

Energy Dispatch control in distribution systems based on *Microgrid* model

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Chapter 1

Abstract

A framework for incorporating renewable energy sources into the traditional economic dispatch problem is presented, which shows the possible advantages of adopting a predictive economic dispatch approach. In particular, simulation of the economic dispatch solution for a microgrid system with both solar and wind technologies as well as battery storage systems, illustrates the conditions under which the operation of power systems, with conventional economic dispatch algorithms do not provide a suitable solution. In addition, the purposed predictive strategy shows that renewable resources can lead to high economical benefits even under high uncertainty, as long as penetration levels of intermittent resources increase significantly.

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Chapter 2

Objectives

2.1 General Objective

Design and implement model predictive control(MPC) strategies in order to perform the economic dispatch of generators in a microgrid. Those strategies will be inspired in the conventional optimization techniques as well as in game theory.

2.2 Specific objectives

- Performe the identification model of a microgrid for the economic dispatch problem.
- Implement model predictive control algorithms that solve the dispatch problems of the generators in a microgrid when it has trade with an utility company, distributed energy surces and storage systems.
- Compare the development of the diferent MPC controllers, evaluating economical, system stability and efficiency performance.

Chapter 3

Introduction

Planning and operation of power systems are going through important transformation due to: i) the advances in electronics and information technologies that make it possible to infer customer behavior from real time data turning them into potential active agents of the system ; ii) the fast growth in energy demand that must be satisfied without incurring in investment costs that are infeasible for utility companies. iii) The high environmental awareness, which leads to the integration of new clean sources for power generation [3, 17]. The motivation of this paper is to understand the possibilities and challenges that emerge in the context of the item iii. for designing optimal solutions that bring the possibility to integrate high levels of renewable energy sources efficiently.

Smart grids emerge as a solution to incorporate diverse technological advances into the power system in order to build a grid based on remote sensing, control and automation. The smart grid proposes an optimized and safer operation by changing the top-down centralized architecture (generation to load) in favor for a decentralized structure where new energy resources can be placed near the consumption points [7]. Distributed generation allows for a more robust operation of the system because it can better handle damages due to generation and infrastructure (e.g. via reconfiguration). Additionally, it may reduce transmission losses due to the generally shorter path between generation and load [15].

Due to the considerable cost reductions and the rapid deployment of many renewable energy technologies, the incorporation of energy sources (like wind and solar) into the power grid has become an important topic of discussion for public and environmental regulators around the world. Many countries in Europe and North America have declared ambitious goals in terms of renewable energy integration. For example, in 2011, the state of California signed a commitment saying that 33% of its electricity must come from renewable sources by 2020 [5, 12, 13].

The advantages of renewable energy technologies are well known: for example, after the initial capital investment there is essentially no cost associated with energy production taking into account that the maintenance cost can be despised.

Moreover, wind and solar technologies are considered clean energy sources and replacing part of the conventional power generation with it will help to reduce the emission of green house gases, in particular compared to the traditional energy generation through coal. As the use of intermittent generation increases, there exist undesired consequences that have not been well established so far and affect both the operation cost and safety of power systems.

For instance, meeting the power balance between supply and demand is a complex task, given the natural variability of renewable resources. The need to reserve energy that supports the system when the renewable sources are not available grows rapidly, often increasing the total generation and operation costs of a system that combines renewable and traditional generation sources.

Inherent characteristics of renewable energy sources such as the high uncertainty surrounding solar irradiance and wind availability, the actual low penetration levels, and the economical benefits suggest that they ought to be treated as non-dispatchable negative loads. This assumption means that after installing one renewable unit, it has to produce as much energy as it can in order to reduce the cost of operating conventional fossil fuel-based generation and recover the investment cost as soon as possible.

Until now this assumption has been valid, but the increasing presence of renewable energy sources such as wind and solar into the existing electricity grid has raised new challenges for the power system operation (e.g. economic dispatch) which require different optimization tools from those previously used. Since the economic dispatch problem has decades of development and it is a well understood optimization problem, the research in the last years has focused on developing optimization algorithms to improve the solutions of the energy resource allocation with less computational cost.

Until recently, most of the work focused on heuristic techniques such as genetic algorithms, particle swarm optimization, and neural networks [1, 9, 10, 14, 16]. But the intermittent nature of the renewable energy sources, changes the characteristics of the dispatch problem and requires new models that characterize and manage the variability on the dispatch of solar and wind technologies and affords the possibility to maximize its use without increasing the generation cost and guarantee a safe operation.

In particular, since the ability to predict the availability of renewable sources in the medium and long term is limited, renewable energy generators cannot be treated like the conventional fully-dispatchable generators, rising the need to model and operate renewable generation in new ways. Due to the fact that the high uncertainty and variability of the generation capacity from the wind and photovoltaic generators has a direct impact on the short-term frequency regulation (safety) and long-term conventional generation scheduling (generation cost), a non-optimal economic dispatch solution will derive in both, technical and economical operation problems.

In recent years, different works have posed this challenge [11, 18]. In [18], the authors propose to treat intermittent energy sources as a controllable generator using a power control system operated by electronic inverters which decides the power level in order to control the dispatch of renewable generators based on the dynamics given by the prediction of the resources availability (wind or solar). The resulting solution is to dispatch the least amount of power that allows compensating variations between the expected (forecasted) and the real energy consumption by the load nodes. With this control strategy, the use of costly conventional generators (like gas plants), which have the capacity to quickly change the power level in between two instances of time is minimized, and maximizes the dispatch of the most economical generators (coal plants), which require longer time intervals to modify the power level that they deliver.

The main objective of this paper is to show the behavioral and technical difficulties that emerge in a low scale power system (microgrid) that incorporates a high percentage of

renewable energy sources into its generation portfolio. By comparing a conventional static dispatch model with an proposed cascade model predictive control strategy (MPC), it is possible to illustrate the reason and benefit of adopting a dynamical predictive approach to solve the economic dispatch problem. Then, two optimization techniques based on classical optimization and, game theory inspired algorithm are evaluated in order to compare the dynamic resource allocation solution and the computational time.

Simulation results demonstrate that the conventional dispatch and the MPC algorithm have a similar performance when the penetration of intermittent resources into the microgrid is low. As penetration level grows, the high ramp events on the renewable sources make the conventional dispatch solution increasingly less viable. In contrast, the economic dispatch solved by MPC can handle the integration of high intermittent resources, taking advantage of the look ahead optimization and the direct control of the renewable source outputs.

Chapter 4

Framework

4.1 System description

The microgrid model is by definition the placing of small scale energy generators grouped close to the consumption points in an energy distribution system. This grouping can work connected to the main energy grid as well as isolated from it. In both scenarios, the main purpose of a microgrid is to guarantee a safe, reliable, and efficient operation while ensuring certain technical and economic criteria [2, 8].

Figure 4.1 shows the scheme of a microgrid that integrates different electric elements which interact together such as: a connection to the main grid; the energy generation and consumption nodes. For example, if the connection to the main grid can be closed for certain moments, then it is a grid connected microgrid (See Figure 4.1a). On the other hand, if the main grid connection is not allowed, that system is called an island microgrid (See Figure 4.1b). Additionally, the energy generation nodes are composed by: conventional generators (such as thermoelectric generators, diesel generators, or nuclear generators) and renewable energy generators (such as solar photovoltaic panels and wind turbines, for which the generation capacity is variable and depends on climatic conditions). Load nodes are also divided into two types: non-controllable nodes or sensitive loads, which have an inelastic demand of energy, and controllable nodes, which have a variable elasticity, meaning that they are disposed to vary their energy consumption in reaction to the changes in price or incentives that are given by the utility company to the users. Finally, the battery storage system is a particular element of the microgrid which can be both a generation element as well as a consumption node, depending if the storage system is charging or discharging.

The remain of this work is focused on grid connected microgrids (See Figure 4.1a) and how they could be an efficient integration of renewable energy sources in the generation side on this scenario. Also, the consumption side is restricted to non controllable loads so the flexibility of the load side is not take into account.

The operation of the microgrid from the point of view of control systems is divided into three levels: the first is in charge of performing local control tasks on the generators, tracking the reference power in real time; the second level contains the power and frequency control,

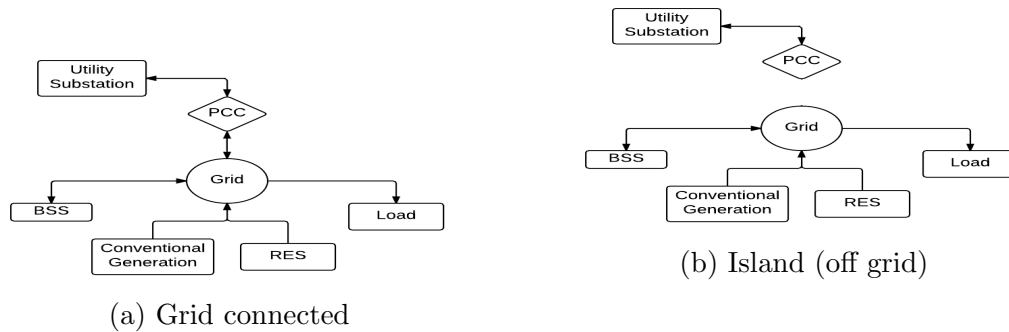


Figure 4.1 Microgrid general block diagram

which is responsible for regulating the frequency of the system by managing power set point of energy reserve sources and preventing that deviations from the nominal frequency (caused by the power variations) exceed the permitted limits leading to a risk situation for the functioning of the system; in the third level there is the dispatch control of the generators, which seeks to maximize the utility of each energy generating agent (or minimize system production costs), subject to restrictions of energy balance between the generated power and the power demand, and to the technical constraints of the energy resource operation (generators).

4.2 Problem Description

Economic dispatch treats the problem of dynamic resource (energy) allocation, where a set of generation units must satisfy the energy demand in a given moment at the most economical solution. As the demand grows, the incorporation of more costly sources of energy is necessary. In the context of microgrids, renewable energy sources are planned as a favorable solution to lower the generation costs as well as the carbon dioxide costs.

The introduction of technologies based in renewable energy sources (RES) involves big challenges to the safety and economical operation of the existing energy systems, in particular, due to the difficulty of predicting the long term availability of these resources. The lack of prediction causes big fluctuations in the power delivered by the generators in short-time intervals (in the order of minutes). This situation force the microgrid system to keep large quantities of energy reserves in order to respond quickly to changes in energy levels form the renewable sources. In general, generators that have this capacity are expensive and as a consequence, the economic benefit of implementing microgrids based on renewable is reduced.

Additionally, in the economical energy dispatch operation there are penalties for deviating from the programmed power quantity to the final delivered power in a given instant. Therefore, intermittent resources that have high variability are at risk of suffering constantly from these penalties. One challenge involved in economic dispatch, is to achieve an effective integration of the intermittent energy sources such that the use of costly energy reserves and penalties due to mistakes in the power balance are minimized. So far, the traditional operation of renewable energy resources does not pay much attention to that problem and absorbs all the power coming from intermittent resources. This is because the penetration level in the majority of countries is less than 8%. It is expected that this procedure will

not be acceptable in the future of power systems and the generation level of intermittent resources has to be part of the decision variables.

Given that the behavior of these technologies vary constantly in time it would be more desirable to perform dynamically the optimization routine for the economic dispatch. For that reason a model predictive control (MPC) based strategy is used as the tool for dynamic scheduling the generation output of both conventional and renewable sources taking into account the advantage that this technique uses the information of the predicted future behavior of the system in order to adjust the dispatch allocation, handling disturbances (renewable sources variability).

Taking into account that the sources of renewable energy often present a very variable unpredictable behavior, it is necessary to study the performance of these sources. First the characterization of their variability and an analysis how they impact the behavior of the economic dispatch in a microgrid system. Previous work has tackled the problem of one specific microgrid configuration, in terms of a specific set of generators, and in most cases the wind and solar data corresponds to a particular day. These studies, however, do not show a general view of the real impact of the proposed solutions that can be applied in a wide range of microgrid applications. The work presented in Appendix A, seeks to understand the RES behavior by studying multiple wind and solar information from various locations across the United States, and characterizes the variability of those renewable sources.

Appendix A, introduces the characteristic and behavior of the RES in order to understand its effect on the economic dispatch of microgrids that include significantly RES penetration level into its generation portfolio. The study was divided into parts, first different meteorological stations were selected to study the behavior of the solar irradiance and the wind speed real data. Second, a set of RES simulated data from the Renewable Energy Sources Laboratory (NREL) RES integration study was used to complete the analysis. The study shows that if the empirical data of the wind speed and solar irradiance at some specific location has a lot of variability (which means that the difference in magnitude between consecutive steps is high) and low availability (which means that in magnitude the renewable energy source is low and do not provide a good energy production), then those locations do not constitute representative spots to continue the investigation with that information, given that the energy that can be take advantage from the RES is very low then even if the penetration level grow considerably the impact of the RES production is limited. On the other hand, the simulated data shows less variability on the RES while a significant improvement on the RES availability, especially on the wind speed source.

The following variables and parameters are used in the formulation of the problem:

Notation	Description	Units
n	Number of conventional generators.	
m	Number of renewable generators.	
T	Prediction horizon for the MPC.	
$P_i^c(k)$	Generated power by the conventional generator i at the instant $k, i = 1, 2, \dots, N$.	(MW)
$\overline{P_i^c}$	Maximum generated power by the conventional generator i at the instant $k, i = 1, 2, \dots, N$.	(MW)
ΔU_i^c	Conventional generation input of the i conventional generator, at the instant	(MW)
ΔU_j^r	RES input of the j RES generator, at the instant $k, j = 1, 2, \dots, M$.	(MW)
$P_j^r(k)$	Generated power by the renewable generator j at the instant $k, j = 1, 2, \dots, M$.	(MW)
$\overline{\hat{P}_j^r(k)}$	Maximum predicted power from the renewable generator j for the instant k .	(MW)
$\bar{P}_j^r(k)$	Scheduled power for the renewable generator j for the instant k .	(MW)
$\hat{P}_j^r(k)$	Power prediction of renewable generator j para el instante k .	(MW)
$C_i(P_i^c(k))$	Production cost for conventional generator i supplying $P_i^c(k)$ power at the instant $k, i = 1, 2, \dots, N$.	(\\$)
R_i	Ramp rate limit for a generator i in an interval of time $\Delta\tau$. $i = 1, 2, \dots, N$	(MW/ $\Delta\tau$)
$L(k)$	Demand of power ($L(k) = L^{nc}(k) + L^c(k)$) en el instante k .	(MW)
$L^c(k)$	Controllable load node	(MW)
$L^{nc}(k)$	Non-controllable load node	(MW)
$\hat{L}(k)$	Forecasted demand of power of the load nodes at instant k .	(MW)
$\Delta\tau$	Time constant corresponding to the sampling frequency e.g. 5 minutos	minuts
$PB^{error}(k)$	Power balance error produced by the forecast error	(MW)
PB^{limit}	Second controller condition to jump from model predictive controller to charging control.	(MW)
$P^{mg}(k)$	Power exchange with the main grid at the instant k .	(MW)
$\overline{P^{bss}}$	Power rated capacity of the storage	(MW/5min)
$P^{ch}(k)$	Charging power of the battery storage system at the instant k .	(MW)
$P^{dch}(k)$	Dis-charging power of the battery storage system at the instant k .	(MW)
$P^{ch}(k)$	Charging power of the battery storage system at the instant k .	(MW)
$P^{dch}(k)$	Dis-charging power of the battery storage system at the instant k .	(MW)
$SOC(k)$	State of charge of the baterrery storage system at the instant k	%
P^{tr}	Trade power between the main grid and the battery storage system for charging purposes.	(MW)
γ	Charge and Discharge efficiency	%

Chapter 5

Economic dispatch in microgrid

5.1 Conventional Economic dispatch

Power systems that have been running for the last century are based on both, conventional generation that is easy to schedule and an uncertainty component introduced by the load. However, due to the seasonal and hourly pattern of the power consumption by different types of users, the experience of the operators, and the forecasting tools it is possible to obtain a very accurate prediction of the upcoming energy demand, not only for the short term but also for the long term [6],[4]. In this context, the power systems operation is modeled as a deterministic system in which the amount of load to serve at every instant is assumed to be almost known.

Since the automation of the electric grid starts in the 50s, when the first computer based control centers appear, the economic dispatch starts to develop a key role in the power system operation. By that time, the system has a medium size then, the optimization procedure involved in the economic dispatch involves a tractable number of operations so that it can be done by traditional optimization algorithms such as linear programming.

Later, the power system experiences a huge expansion and becomes a complex systems not only because of the size but also due to its networks. When the optimization problem of the economic dispatch became a large scale problem, the traditional algorithms no longer worked because of the computational cost. Besides this, in the late 90s heuristic optimization (e.g. genetic algorithms, and particle swarm optimization) began to gain acceptance in the research community, so they start to be used in the solution of the economic dispatch problem.

5.1.1 Mathematical formulation

The economic dispatch problem for the conventional power system is posed as an optimization problem (See e.q. (5.1) to e.q. (5.5). E.q. (5.1) corresponds to the function that must be minimize. As mentioned before the renewable energy sources are treated as having a zero operational cost given that the capital cost is not taken into account. Therefore the operation cost of the microgrid is the operation cost of the conventional generators which is performed by the quadratic cost function shown on the e.q. (5.6). The quadratic cost function relates the conventional generation fixed cost, the proportion of the power produced and the cost associated to the fuel cost.

The economic dispatch must be solved at every instant satisfying the following constraints: e.q. (5.2) refers to the power balance of the system and e.q. (5.3) to e.q. (5.5) are the technical constraints of the conventional generation units.

$$\min_{U_i^c(k)} \sum_{i=1}^n C_i(P_i^c(k)) \quad (5.1)$$

s.t.

$$\sum_{i=1}^n P_i^c(k) = \hat{L}(k) \quad (5.2)$$

$$P_i^c(k) = P_i^c(k-1) + \Delta U_i^c \quad (5.3)$$

$$0 \leq P_i^c \leq \bar{P}_i^c \quad (5.4)$$

$$|P_i^c(k) - P_i^c(k-1)| \leq R_i \Delta \tau \quad (5.5)$$

$$C_i(P_i^c(k)) = a_0 P_i^c(k)^2 + a_1 P_i^c(k) + a_2 \quad (5.6)$$

Recall that the microgrid system intent to create small power subsystems, where the grouping of some generators and customers are placed at the same location. The fact that the size of the microgrids is small allows us to say that it is reasonable to solve the economic dispatch with traditional optimization algorithms instead of heuristic techniques.

In real time operation, it is not possible to guarantee the power balance restriction equal to zero because of the forecasting errors. Thus, the power balance error matching task is performed so that the units that are in charge of tracking the load between the economic dispatch operating points are able to change their power dispatch set point rapidly. The range of time of the load variations goes from 1 minute to 1 hour. The generators that have the potential to switch their output in that way are typically the most expensive, and for that reason it is always desirable to have the minimum power balance errors.

When the renewable energy sources are introduced into the existing power system, the dispatch policy adopted by the utilities, in order to minimize costs is to take them as negative loads which deliver all its total (variable) capacity at any instant of time and then use the conventional generation to compensate the variability of both load consumption and renewable resources (generation side).

The optimization procedure including the intermittent generation is shown in e.q (5.7) to e.q. (5.13), where the optimization problem change the e.q.(5.2) a with the eq.(5.8). In this case, a prediction for the power availability of the renewable sources is required (See e.q. 5.19) in order to compute the vaule of the RES amount of energy available for the next economic dispatch operation point. Because of the main objective of the project is not related with the forecast study, simple auto-regressive moving average models are used to performe the load consumption and the output capacities of the solar and wind generators (See the Appendix B).

$$\min_{U_i^c(k)} \sum_{i=1}^n C_i(P_i^c(k)) \quad (5.7)$$

s.t.

$$\sum_{i=1}^N P_i^c(k) = \hat{L}(k) - \sum_{j=1}^M \hat{P}_j^r(k) \quad (5.8)$$

$$P_i^c(k+1) = P_i^c(k) + \Delta U_i^c \quad (5.9)$$

$$\hat{L}(k+1) = f(L(k), L(k-1), \dots, L(k-nb)) \quad (5.10)$$

$$\hat{P}_j^r(k+1) = h(P_j^r(k), P_j^r(k-1), \dots, P_j^r(k-nb)) \quad (5.11)$$

$$0 \leq P_i^c(k) \leq \bar{P}_i^c \quad (5.12)$$

$$|P_i^c(k) - P_i^c(k-1)| \leq R_i * \Delta\tau \quad (5.13)$$

5.2 Economic dispatch using MPC

Model predictive control (MPC) is a widely used control technique for multi variable constrained problems and its effectiveness has been demonstrated particularly in the field of process control. The structure of the control structure is shown in figure 5.1 in which the total load consumption must be equal to the resulting power generation of the microgrid in order to minimize the power balance error, and works as follow: First, the system to be controlled has to be modeled so that a prediction of the future outputs can be performed. In most cases, the modeling is done through a linear state space representation of the form $x(k+1) = Ax(k) + Bu(k)$, where $x(k) \in R^n$ are the states and $u(k) \in R^m$ denote the inputs. Secondly there is an optimization block that calculates the input to the plant, ensuring a secure and desirable behavior (minimizing an objective or control task) of the system.

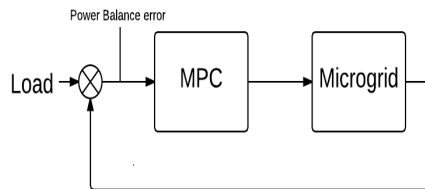


Figure 5.1 MPC loop

At any specific time the MPC process the information from the past states and outputs in order to compute the solution of the optimal control problem. Then this solution fed to the model which produces a future output. After, the optimization box receives the predicted

values and solves the problem again, the process continues until the solution is complete for the whole control horizon (T). When the MPC solution is ready, only the first step is applied to the plant, then new measurement outputs are introduced to the controller and the finite-horizon optimization cycle starts again as shown in Figure 5.2.

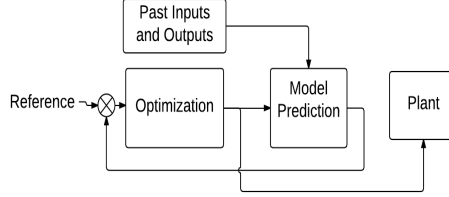


Figure 5.2 MPC block diagram adapted from Camacho y Bordons

By adopting the MPC strategy the economic dispatch problem is reformulated as shown in e.q. (5.14) to e.q. (5.22).

$$\min_{U(k)} \sum_{k=1}^T \sum_{i=1}^n C_i(P_i^c(k)) \quad (5.14)$$

s. t.

$$\sum_{i=1}^n P_i^c(k) + \sum_{j=1}^m P_j^r(k) = \hat{L}(k) \quad (5.15)$$

$$P_i^c(k+1) = P_i^c(k) + \Delta U_i^c \quad (5.16)$$

$$P_j^r(k+1) = P_j^r(k) + \Delta U_j^r \quad (5.17)$$

$$\hat{L}(k+1) = f(L(k), L(k-1), \dots, L(k-nb)) \quad (5.18)$$

$$\hat{P}_j^r(k+1) = h(P_j^r(k), P_j^r(k-1), \dots, P_j^r(k-nb)) \quad (5.19)$$

$$0 \leq P_j^r(k) \leq \overline{P}_j^r(k) \quad (5.20)$$

$$0 \leq P^c \leq \overline{P}_i^c(k) \quad (5.21)$$

$$|P_i^c(k+1) - P_i^c(k)| \leq R_i \Delta \tau \quad (5.22)$$

As in the previous economic dispatch formulations in this case the cost function corresponds only to the conventional generation cost and is modeled by the e.q. (5.6). The main differences with the previous formulation are that the MPC algorithm is a dynamic optimization problem carried out over a prediction horizon T (see e.q. (5.14)), so the optimization problem is computed for the entire prediction horizon taking into account the conventional and renewable energy sources dynamics and the customers needs of power demanded. In addition, the renewable energy resources are included into the decision variables so that the power generation output of these sources can vary from the variable maximum predicted capacity at any instant k (see e.q. (5.20)) and the power balance equation is define as e.q. (5.15). The

prediction for the power availability of those sources is required (See e.q. (5.19)) in order to complete the dynamics of the whole economic dispatch problem.

The prediction values of the load and the renewable energy sources are computed using historical data, as it is mention on the appendix B. The past data that fed the auto-regresive moving average models starts with the measure data as shown in e.q. (5.19) and e.q. (5.18). Then when k goes up to T the predicted values are included into the past data for the prediction procedure, so that, the e.q. (5.19) and e.q. (5.18) changes to e.q. (5.24) and e.q. (5.23)

$$\begin{aligned} \hat{L}(k+1) &= f(\hat{L}(k), \hat{L}(k-1), \dots, \hat{L}(k-T-1), \\ &L(k-T-2), \dots, L(k-nb)), k = T-1 \end{aligned} \quad (5.23)$$

$$\begin{aligned} \hat{P}_j^r(k+1) &= h(P_j^r(\hat{k}), \hat{P}_j^r(k-1), \dots, \hat{P}_j^r(k-T-1), \\ &P_j^r(k-T-2), \dots, P_j^r(k-nb)), k = T-1 \end{aligned} \quad (5.24)$$

In order to quantify the effect of the economic dispatch performed under diferent conditions of renewable energy sources in the next section the data used in the study of the appendix A is used to performed the economic dispatch. This work shows three different scenarios that illustrates the behavior of the economic dispatch in microgrd integrating the renewable energy sources.

5.3 Economic dispatch comparing different simulated Data

Data from the five locations of the simulated data, California, Oregon, Texas, Colorado, and Utah are used to feed the microgrid for the economic dispatch simulations. In this simulated data scenario three simulations that shows different performance levels of the MPC strategy are carried out.

Figure 5.3 shows the behavior of the different generators dispatch allocation during three days of March at California. The cost difference between the conventional static dispatch and the MPC savings varies from 0.65 % when there is no RES, up to 9.27 % when the RES penetration level is 100%. Also, the prediction horizon exhibits savings of 0.42 % up to 2.98 under the same RES penetration level conditions which demonstrate the effect and effectiveness of the predictive dispatch. It is clear that for RES behavior like this the MPC improves considerably the economic dispatch solution.

In particular, Figures 5.3c and 5.3d illustrate the RES dispatch differences between both optimization techniques. Note that the RES shows high variability specially during the midday. Also the availability oscillates between middle and high amount of power range. That RES behavior provokes high power balance errors (See Figure 5.3a bottom plot). In contrast, the MPC strategy guarantees zero power balance error by reducing the RES output during high ramp peaks (e.g. from 40 to 70 time samples or from 370 to 430 time samples) sacrificing the exploit of all its availability.

Figure 5.3b shows the same characteristic presented in the empirical measured data scenario when the maximum economic benefit is achieved, and can be summarized in the following results: i) the gas unit operated with the conventional dispatch has to deliver high

amount of power e.g. 6 MW in order to compensate the high RES variations. ii) The MPC allows to reduce significantly the gas unit peaks. iii) The Coal unit 2 operation is improved by the MPC allowing dispatching more power from this generator. Those are the main MPC actions that allow to reduce the operation cost of the economic dispatch.

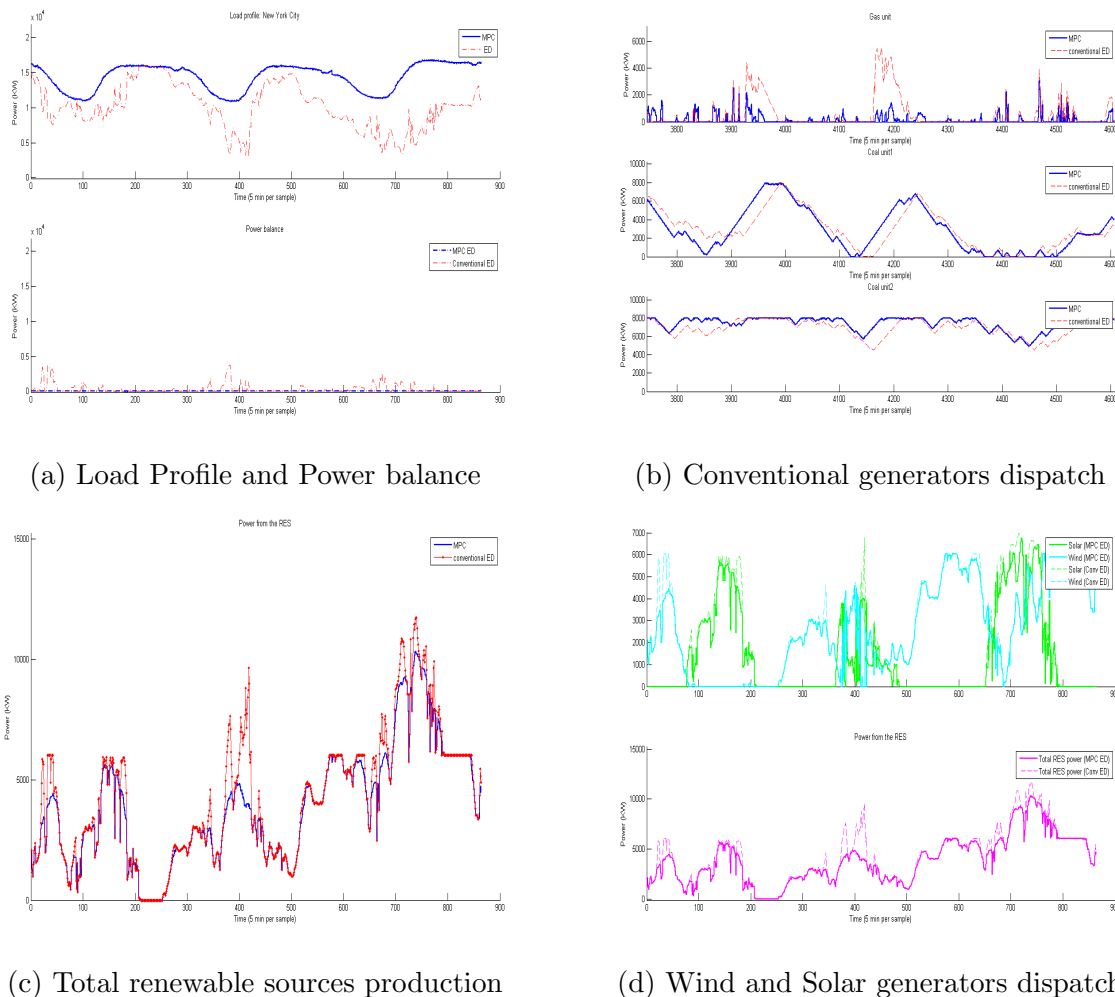


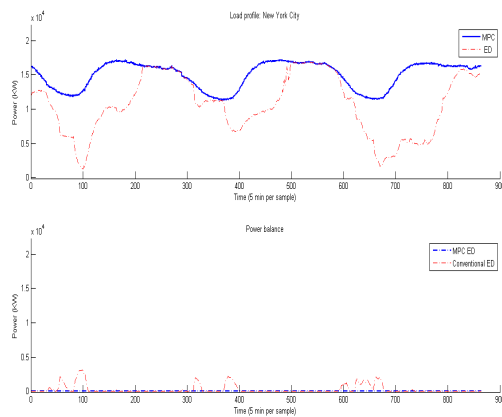
Figure 5.3 Microgrid operation at the end of March with California data

Next, Figure 5.4 shows the result for a simulation that produce a typically mid-range economic benefit. The results are obtained from three different days of March, again at California. In this case, the economic benefit of MPC economic dispatch starts with savings equal to 0.68% when no RES is introduced and goes up to 7.44% of the total operation cost when the RES install capacity corresponds to 100% of the maximum load. Also, an important saving is found with the prediction horizon were the economic savings are 0.39% with 0% of RES up to 4.90% with 100% of RES. Note that these results are as good as the best performance achieved with the empirical data in spite of it corresponding to the mid-range performance.

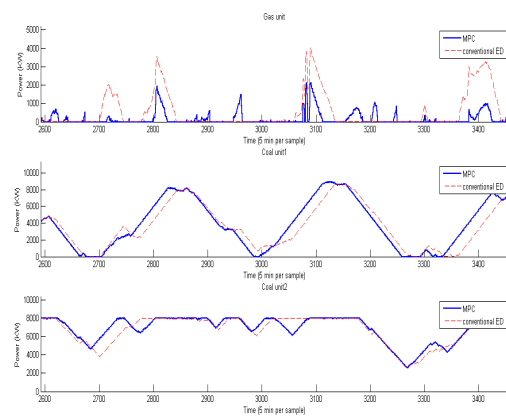
Figures 5.3c and 5.3d show a set of RES that has great amount of power but with lower

variability. This can explain why the economic benefit is lower than the previous case. In terms of security, Figures 5.4a bottom and 5.4c allow to say that the the MPC technique contributes to avoid the power balance error by reallocating the RES production in critical moments (e.g. lower the use of RES from 90 samples to 130 samples and after 320 samples to 350 samples).

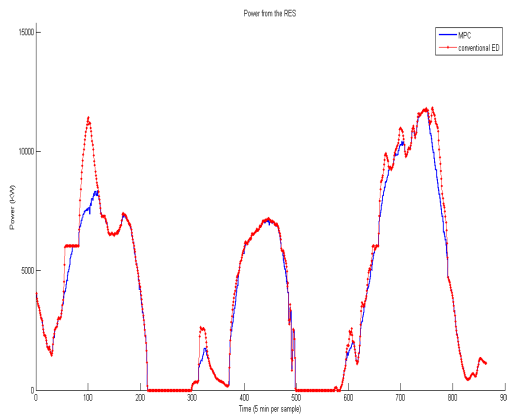
Another effect of the MPC dispatch strategy is shown in Figures 5.4a bottom and 5.4c, when from the 780 sample to 800 sample the MPC reduces the RES dispatch and reallocates coal unit 1 generation allowing to lower the gas unit output. In Figure 5.4a bottom it can be appreciated that the power balance error is 0 even with the conventional dispatch in the range of time specified above, so the action produced by the MPC is for economic purposes only.



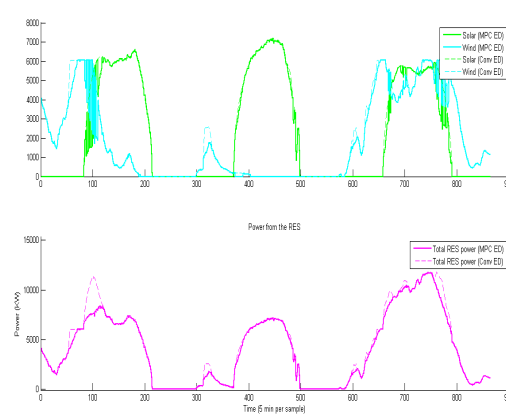
(a) Load Profile and Power balance



(b) Conventional generators dispatch



(c) Total renewable sources production



(d) Wind and Solar generators dispatch

Figure 5.4 Microgrid operation in the middle of March with California data

Finally, an example of a low performance of the MPC against the conventional static economic dispatch is presented in Figure 5.5. The simulated RES data for this simulation corresponds to three days of April at Utah state. In this scenario the total operation cost and

prediction horizon difference when the microgrid does not include RES are 0.62% and 0.32% respectively, and goes up to 2.24% and 0.65% when the RES installed capacity is 100%. These results shows a considerable reduction of the MPC improvement on the economic dispatch solution compared to the previous examples of simulated data. That fact proves that it is not possible to generalize and quantify easily the advantages of the predictive strategy versus the conventional dispatch with small amount of RES data as it is always presented in related papers.

Figures 5.5c and 5.5d shows that variability and availability of the RES are low. With this pattern of the RES behavior, it can be seen in Figure 5.5b that the conventional and predictive dispatch solution produces almost the same solution, which demonstrates that the MPC has less operation capacity. The lack of RES variability makes the that the gas unit production is low, then the economic benefit of reducing its output due to the MPC action is small. In addition, since the few RES ramp events go up and down in short time, the gas unit can follow those variations easily and in a cost effective way.

Figure 5.5a bottom shows that the power balance is close to zero even with the conventional dispatch due to the low variability produced by RES. In this case, the conventional generation can ramp up and down keeping track of the load and RES changes, limiting even more the advantages of the MPC strategy against the conventional dispatch.

Table 5.1 shows the economic benefit of implementin the MPC instead of the conventional static optimization for the microgrid operation with a different percentage of RES penetration. Note that the location in California has a high mean value for all the RES penetration level suggesting that this site is the most suitable for the MPC adoption.

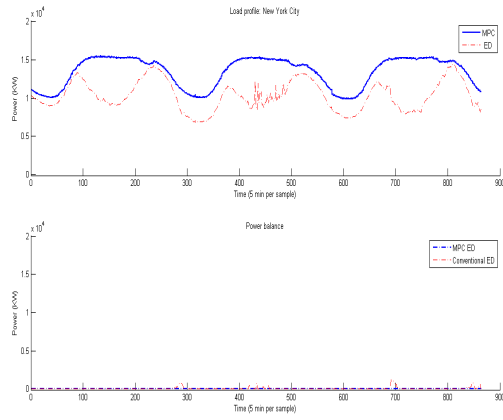
From Table 5.1, if the RES penetration level of the microgrid is up to 40% it is possible to achieve significant economic savings. The results obtained here demonstrate that the different locations presented here are appropriate places to take the advantage not only of the RES integration into the microgrid but also of the MPC optimization implementation.

Table 5.1 Simulated data 1 mean and std results of operation cost difference using simulated RES data

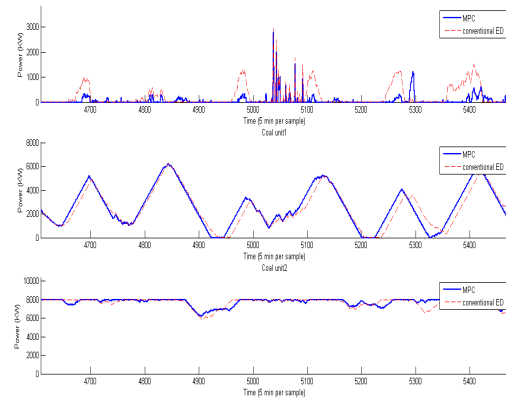
<i>Conv Vs MPC cost difference (%)</i>										
RES (%)	<i>California</i>		<i>Texas</i>		<i>Colorado</i>		<i>Utah</i>		<i>Oregon</i>	
	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>
0	0,64	0,27	0,60	0,29	0,79	0,25	0,64	0,26	0,63	0,28
40	1,59	0,50	0,97	0,27	1,07	0,59	1,21	0,78	1,28	0,58
80	4,78	0,97	2,78	0,62	3,07	0,60	3,26	0,95	3,41	1,23
100	7,12	1,40	4,19	1,10	4,89	0,89	4,95	1,23	5,00	1,71

Table 5.2 shows the benefit that the prediction horizon can produce for the different economic dispatch solutions. For example, assuming a RES penetration level of 100% the benefit derived from setting a prediction horizon greater or equal to 72 steps (6 hours) is at least 1.73%. Also, the std deviation results are significant, which allows to reach at some days even higher economic savings from the prediction horizon selection.

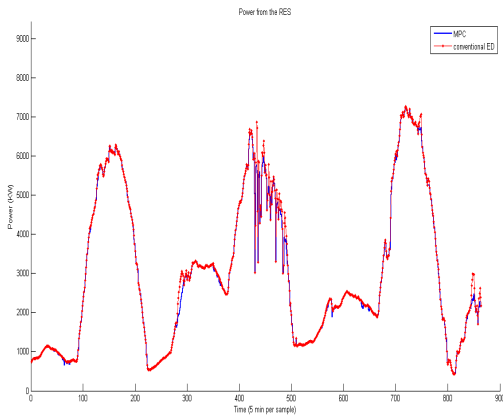
Finally, Table 5.3 illustrate the reserve capacity requirements for the microgrid when it is operated with the conventional dispatch optimization. The reserve capacity results, here



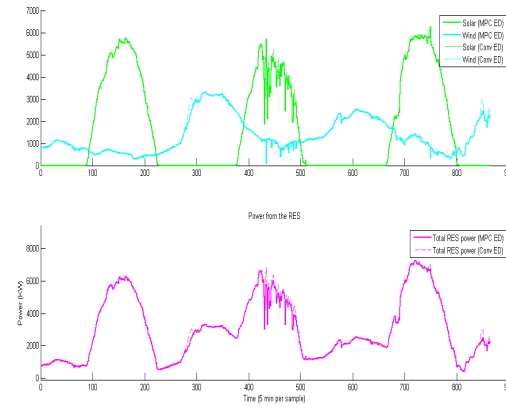
(a) Load Profile and Power balance



(b) Conventional generators dispatch



(c) Total renewable sources production



(d) Wind and Solar generators dispatch

Figure 5.5 Microgrid operation in the middle of April using Utah data

Table 5.2 Simulated data 1 mean and std results of MPC prediction horizon effect

<i>Prediction horizon cost difference (%)</i>										
	<i>California</i>		<i>Texas</i>		<i>Colorado</i>		<i>Utah</i>		<i>Oregon</i>	
RES (%)	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>
0	0,39	0,21	0,40	0,24	0,44	0,20	0,40	0,21	0,39	0,22
20	0,31	0,22	0,26	0,20	0,16	0,14	0,35	0,33	0,19	0,15
40	0,61	0,30	0,32	0,21	0,25	0,24	0,55	0,60	0,36	0,33
60	1,21	0,43	0,48	0,29	0,45	0,34	1,00	0,82	0,76	0,57
80	1,96	0,54	0,99	0,55	0,72	0,40	1,53	0,78	1,28	0,70
100	3,42	1,18	1,73	0,72	1,75	0,82	2,42	0,65	1,95	0,82

for penetration level up to 60% shows that the reserve capacity must be greater than 10% of the maximum load which is an significant amount of power to have idle only for security

Table 5.3 Simulated data 1 mean and std results of reserve capacity requirements

<i>Reserve Capacity (%)</i>										
	<i>California</i>		<i>Texas</i>		<i>Colorado</i>		<i>Utah</i>		<i>Oregon</i>	
RES (%)	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>	<i>Mean</i>	<i>Std</i>
0	1,87	1,09	1,43	0,85	1,40	0,92	1,77	1,45	1,44	0,84
40	9,85	3,92	6,09	4,28	8,46	3,26	5,84	3,50	11,20	5,46
80	25,34	7,54	16,26	6,55	19,86	5,97	14,33	6,66	23,36	9,86
100	35,85	10,00	21,78	7,69	26,25	7,65	21,40	7,78	29,98	11,93

and safety purposes. This fact produces over cost for the operation of the microgrid.

The conclusions of the first economic dispatch study comparing the conventional dispatch with the predictive control can be summarized as follows:

- As expected, the main results of the cost difference between the conventional static dispatch and the MPC shows that for low RES penetration levels e.g. under 60%, the predictive dispatch do not bring significant improvements to the economic dispatch solution. When the RES contribution to the generation portfolio of the microgrid is low wind and solar generation can add very little flexibility to the generation side, then most of the economic dispatch is done by the conventional generators which have hard ramp rate constraints that limit MPC action. Due to real renewable sources installations has penetration levels up to 20% it is reasonable to understand why those systems continue operating with traditional conventional economic dispatch optimization. Similarly when the MPC is applied to the microgrid operation the prediction horizon became an important parameter that affect the economical solution when the amount of RES power grows.
- When the microgrid operation with RES integrated is performed with MPC, it guarantees the safe operation of the system by ensuring the power balance constraint, this also reduces the reserve capacity needs of the microgrid which can led to an efficient and economic operation. Results shows that for high RES penetration level the predictive dispatch can achieve important economic benefits with mean cost different savings around 5% of the predictive dispatch against the conventional dispatch. Moreover, the outcomes obtained with simulated data indicate that in some particular scenarios the MPC can produce savings up to 15%. Taking into account the costly operation of the power systems, the economic savings obtained with the MPC strategy are significant.

5.4 Proposed predictive dispatch

The principal objective of the economic dispatch is to guarantee a safe and economical operation of the micogrid. Given that the renewable energy sources impose uncertainty and variability on their generation, it is very difficult to achieve an accurate forecast. Given that the forcast errors leds to undesired operating contions in which the power balance error is not zero and there exists scenarios in wich as long as the renewable energy sources grow the

error becomes higher, also due that the renewable energy forecast error leads to undesired mismatches in the power balance errors. It is important to remark that the power balance errors produced in the economic dispatch need to be solved by the secondary control or frequency control but if the amount of error is higher so that the secondary control cannot handle it, then the microgrid system is at high risk of failures. To overcome that difficulty a cascade control strategy proposed was designed and test by simulation.

As shown in the Fig. 5.6 the economic dispatch optimization is divided into two sub-problems: i) First, the microgrid generation side must balance the energy demanded from the load side performing a typical economic dispatch, in this case a model predictive control is implemented to minimize the power balance error. ii) Second, due to the forecast error a remaining quantity of power is still needed to be allocated, for that task an dynamic resource allocation between the main grid and a battery storage system (BSS) is performed. The second controller is explain in the next section.

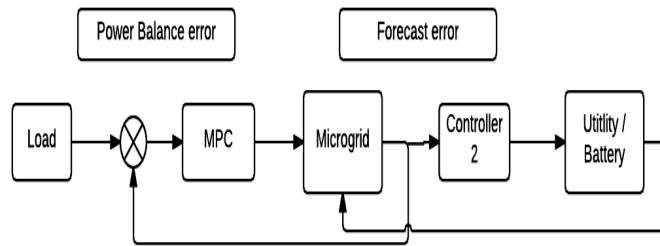


Figure 5.6 Proposed predictive dispatch block diagram

5.5 Power balance error dispatch

Given that the microgrid system in this case must operate as a single controlled unit, and no participation in the power market is done, the main grid is not considered as a dispatchable generation unit but as an extremely large storage system. This formulation let us think the main grid and the battery storage system as the correction units to guarantee the equality constraint between the power generated and the power consumed by the load.

Fig. 5.7 shows the control developed to accomplish the task of allocate the forecast errors after the model predictive control. The power balance error dispatch control is a two stage control that depends on the conditional shown in Fig. 5.7 which is state or level of the power balance error, then if the power balance error is high which means that the system could have stability problems the controller will switch to the MPC2 in order to absorb the power balance error with the storage systems, on the other hand if the power balance error is low so that, the system can handle easily without incurring in safety problem the power balance error will switch to the charging controller.

In other words, when the power balance error is greater or equal to some limit PB^{limit} that corresponds to a safety condition, the conditional switches to yes and the second model

predictive control is performed in order to allocate economically the power balance between the main grid and the battery storage system. Contrary if the power balance error is smaller than the limit PB^{limit} , then the conditional output is set to no and a charging control which intend to charge the battery with power from the main grid is done.

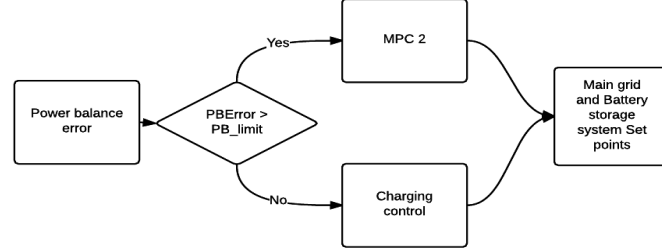


Figure 5.7 Two stages control

5.5.1 Mathematical formulation

The second model predictive control is a dynamic programming that has to allocate the power balance error into the main grid and the battery storage system, it is modeled as an economic dispatch problem similarly to the one presented before. The optimization procedure is presented in the following equations: e.q. (5.25) to e.q. (5.32). In this case the cost function e.q. (5.25) represent a weighed cost function to balance the use of the main grid or the battery. The power balance equation correspond to the equality constraint e.q. (5.26) which guarantee the principal task of this control. The rest of the equations corresponds to the dynamical system and the technical constraints of both the main grid and the battery storage system. For the main grid the dynamical systems is carried out by the difference equation e.q.(5.27), on the other hand the battery system dynamic is modeled by the state of charge (SOC) of the battery that gives the measurement of the capacity in percentage that the battery has at any given point as e.q.(5.28) shows.

$$\min_{\Delta P^{mg}, P^{ch}, P^{dch}} \sum_{k=1}^T \alpha (P^{mg}(k)^2) + \beta (P^{ch}(k)^2 + P^{dch}(k)^2) \quad (5.25)$$

s.t.

$$P^{mg}(k) + P^{ch}(k) - P^{dch}(k) = PB^{error}(k) \quad (5.26)$$

$$P^{mg}(k+1) = P^{mg}(k) + \Delta P^{mg} \quad (5.27)$$

$$SOC(k+1) = SOC(k) + \gamma (P^{ch} / \overline{P^{bss}} - P^{dch} / \overline{P^{bss}}) \quad (5.28)$$

$$P^{ch} \leq \overline{P^{bss}} \quad (5.29)$$

$$P^{dch} \leq \overline{P^{bss}} \quad (5.30)$$

$$P^{ch} \geq 0 \quad (5.31)$$

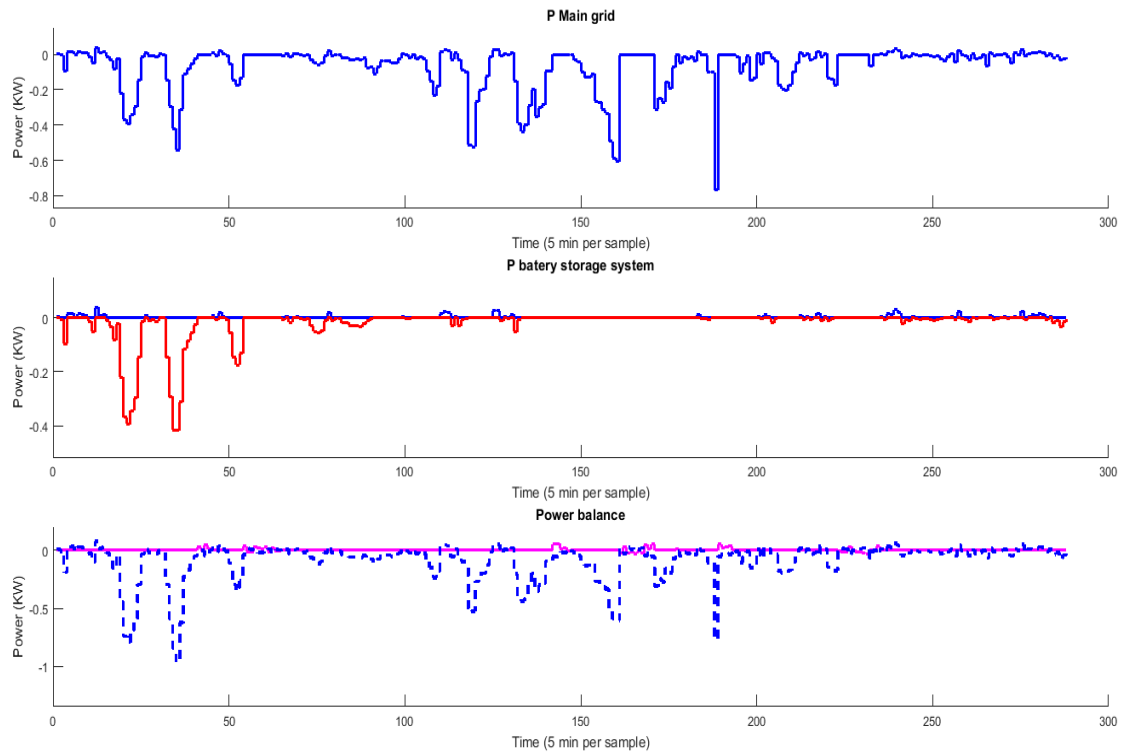
$$P^{dch} \geq 0 \quad (5.32)$$

The result of the implementation of the second model predictive control is shown in the Fig.5.8, this case assumes that no charging control is active. It can be appreciated how the power balance error is equal to zero in the Fig.5.8a (the magenta line), in this scenario the battery remains discharged after the 50 time samples and then only the main grid compensates the difference of the power balance error (See Fig.5.8a). This result motivates the need of a battery charge control.

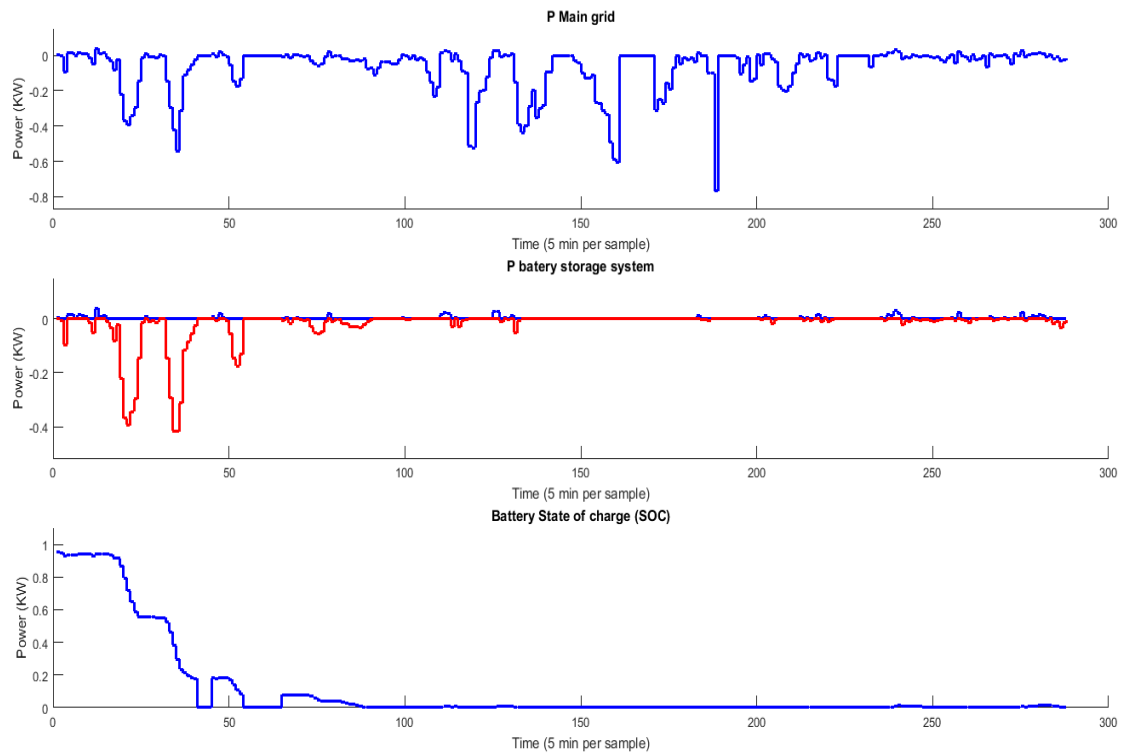
Finally the charging control is defined and follows the next rules stated in e.q. (5.33). First, if the power balance error produced by the renewable energy sources forecast error is greater or equal to the safety limit defined as PB^{limit} and the SOC of the battery is less or equal to the 80% the charging control decides to purchase the fixed amount of power P^{tr} in order to charge the battery. If the past rule is not satisfied then the system does not charge the battery.

$$P^{ch} = \begin{cases} P^{tr}, & \text{if } |PB^{error}| \geq PB^{limit} \\ & SOC(k) \leq 0.8 \\ 0, & \text{otherwise} \end{cases} \quad (5.33)$$

In this case it is clear how the main grid delivers the power that the battery storage system takes to charge the battery, for example after the 50 time samples (see Fig.5.9a). As well as in the previous case the power balance error is going to zero but in this scenario the battery system works the whole simulation for example in the time sample 180 approx the battery discharges in order to reduce the power balance error. Additionally, Fig.5.9b shows the dynamic of the SOC and how it tends to reach the 0.8 % as the charging control imposes that goal.

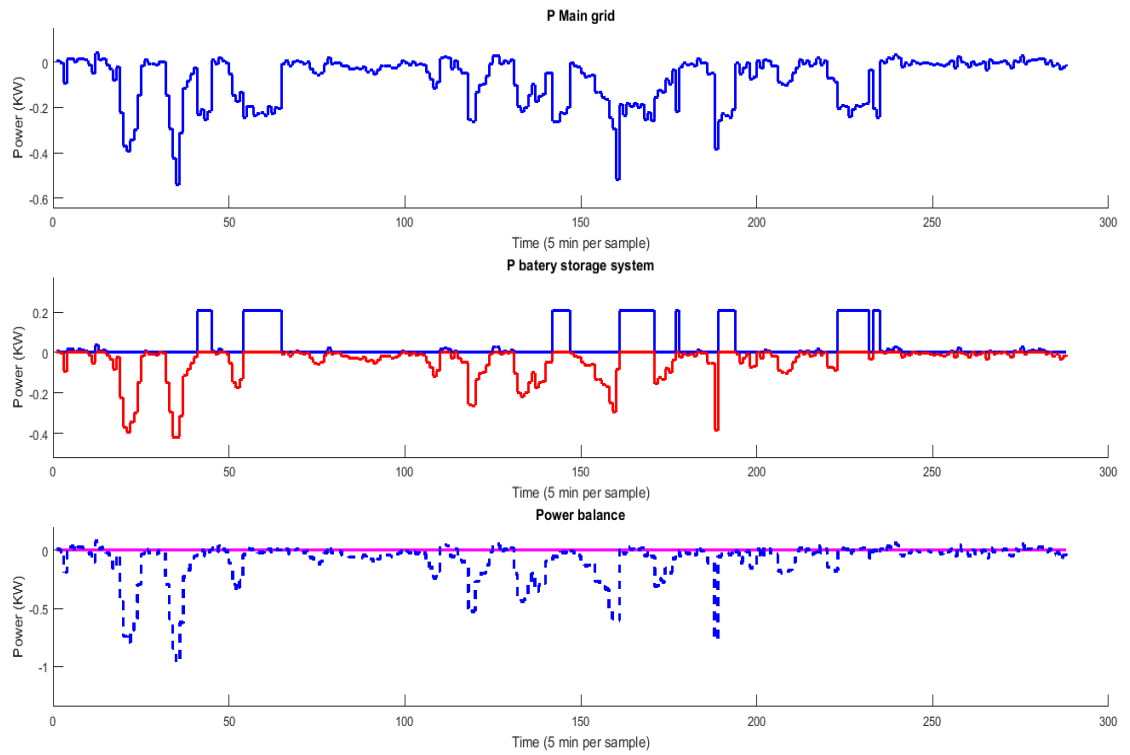


(a) Main grid and battery storage system with power balance error

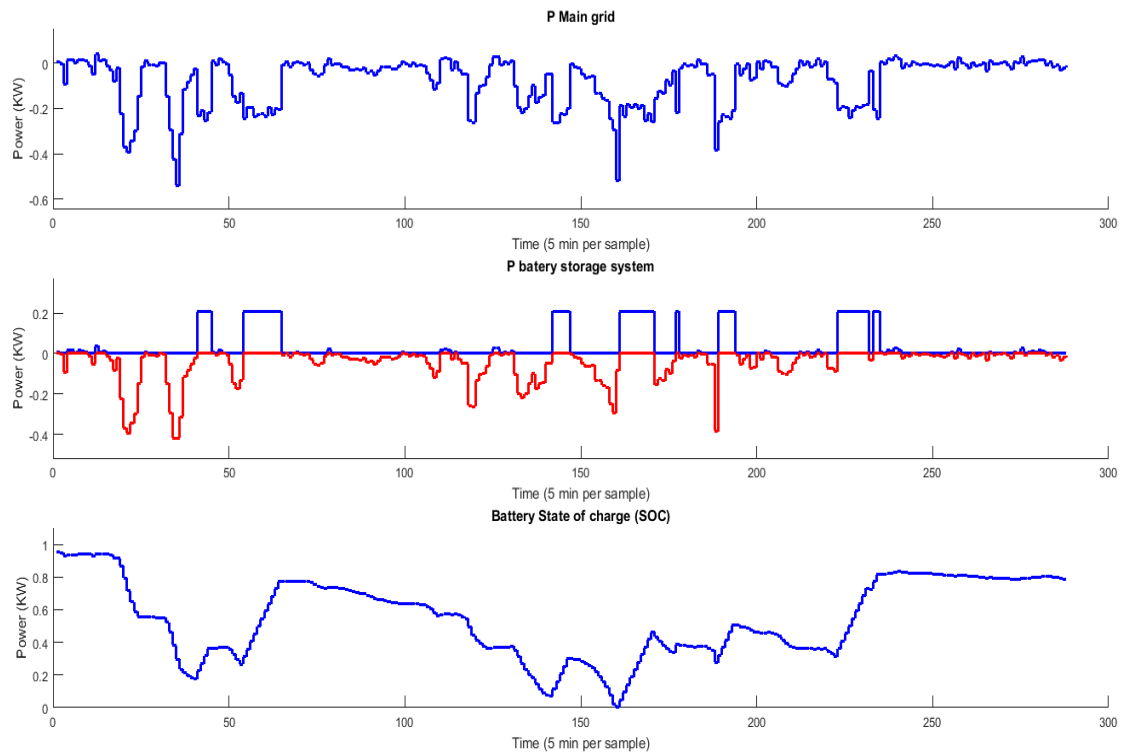


(b) Main grid and battery storage system dynamics

Figure 5.8 Controller 2 without charging control



(a) Main grid and battery storage system with power balance error



(b) Main grid and battery storage system

Figure 5.9 Microgrid general block diagram

Chapter 6

Results

In the following section the simulation results of the whole economic dispatch purposed is presented. As mentioned before the grid connected microgrid modeled in chapter three is used to perform the different simulations. Each simulation correspond to one day operation of 24 hours sampled at 5 minuts. The economic dispatch is solved using the Matlab software in addition the Yalmip toolbox using the gurobi solver are in charge off the optimization calculations. It is important to remark that the objective of the control purposed is to first guarantee a safe operation of the system avoiding the power balance error due to the renewable energy sources forecast errors, second an economical solution of the microgrid operation must be achieved while the integration of the renewable sources grows.

In table 6.1 is shown the principal characteristic of the different scenarios simulated. The most important characteristics that are going to be compared and analyzed are the result of the economic dispatch with and without forecast as well as the ramp rate limit constraint in which a slow ramp rate is compared to a fast ramp rate. Whitin this procedure the conditions in which the predictive controller is a sutable solution for the economic dispatch against to the conventional optimizion are found.

6.1 Ramp rate influence

Table 6.2 shows the result of the different scenarios were the ramp rate limits has two slow and cheapest unit and one expensive fast responsive unit. When the scenario corresponds to a no forecast it means that the information of the future renewable energy source data is known perfectly, on the other hand when the simulation scenario has forecast equal to yes, it means that the future data of the renewable energy sources is product of a prediction process.

It is important to notice that from the set of 5 days of simulation when the economical benefit of the predictive strategy is 99% that means that the conventional solution is infeasible because the optimization technique cannot found a generation combination that could handle the variability of the renewable energy sources so the cost of operation is extremly high which represent the safety and operational cost of this situation. This fact allows to said that the

Simulation	Day (May 2014)	Forecast	Gas generator capacity (MW)	Ram rate
1	5	no	2.5, 2.5, 2.5	slow
		yes	2.5, 2.5, 2.5	slow
2	5	no	2.5, 2.5, 2.5	fast
		yes	2.5, 2.5, 2.5	fast
3	8	no	2.5, 2.5, 2.5	slow
		yes	2.5, 2.5, 2.5	slow
4	8	no	2.5, 2.5, 2.5	fast
		yes	2.5, 2.5, 2.5	fast
5	22	no	2.5, 2.5, 2.5	slow
		yes	2.5, 2.5, 2.5	slow
6	22	no	2.5, 2.5, 2.5	fast
		yes	2.5, 2.5, 2.5	fast
7	28	no	2.5, 2.5, 2.5	slow
		yes	2.5, 2.5, 2.5	slow
8	28	no	2.5, 2.5, 2.5	fast
		yes	2.5, 2.5, 2.5	fast
9	29	no	2.5, 2.5, 2.5	slow
		yes	2.5, 2.5, 2.5	slow
10	29	no	2.5, 2.5, 2.5	fast
		yes	2.5, 2.5, 2.5	fast

Table 6.1 Complete system set of simulations

predictive strategie guarantees a safer operation given that in all the simulation scenarios produce a viable solution for the entire simulation.

The results for the microgrid system with slow generation units show how when the solution of the economic dispatch is solved with the conventional optimization technique it is more costly than the predictive dispatch. Then if the microgrid configuration has slow generation units combined with fast responsive unit always the predictive dispatch produce a better performance against the conventional dispatch both economical and in terms of safety operation.

Also from the same set of simulations, it is found that the predictive dispatch has better results when there is no forecast, this is because the renewable energy source signal has more variability and the model predictive control can decide a better solution to dispatch those generators. When the scenario includes forecast, the smothed signal produced by the forecast method reduce significantly the variability of the original signal thus the predictive dispach do not have many alternatives diferent from dispatch the smothed forecasted signal for the renewable energy signals.

Fig. 6.1 illustrates the behavior of the economic dispatch when the renewable energy sources has a installed capacity corresponding to 100% of penetration level, and there is no

Sim	Forecast	MPC cost (USD)	Conv cost (USD)	MPC cost benefit (%)
1	no	2.99E5	3.034E5	1.3
	yes	2.992E5	3.019E5	0.9
3	no	3.041E5	4.2E6	99
	yes	3.061E5	4.2E6	99
5	no	2.985E5	3.068E5	3
	yes	3.003E5	3.070E5	2.2
7	no	2.970E5	6.7E6	99
	yes	2.997E5	5.7E6	99
9	no	3.987E5	3.055E5	2.3
	yes	3.004E5	3.034E5	1

Table 6.2 Result for slow ramp rate simulations

forecast. From Fig.6.1a it is clear that the predictive strategy anticipate and correct the scheduling of the cheapest units (See unit 1 and unit 2 at 150 time samples) in order to lower the use of the expensive unit. In addition in Fig.6.1b it is shown how the predictive dispatch reduces the power from the renewable energy sources, so that the power balance becomes zero (e.g. simulation from time sample 25 to 35) and the re-scheduling of the conventional generators can be performed (e.g. simulation from time sample 150 to 180).

In this case given that there is no forecast error because it is asumed to be perfectly know, the second controller do not has to compensate any imbalance of energy, then the main grid and the battery remanins in active (See. Fig.??).

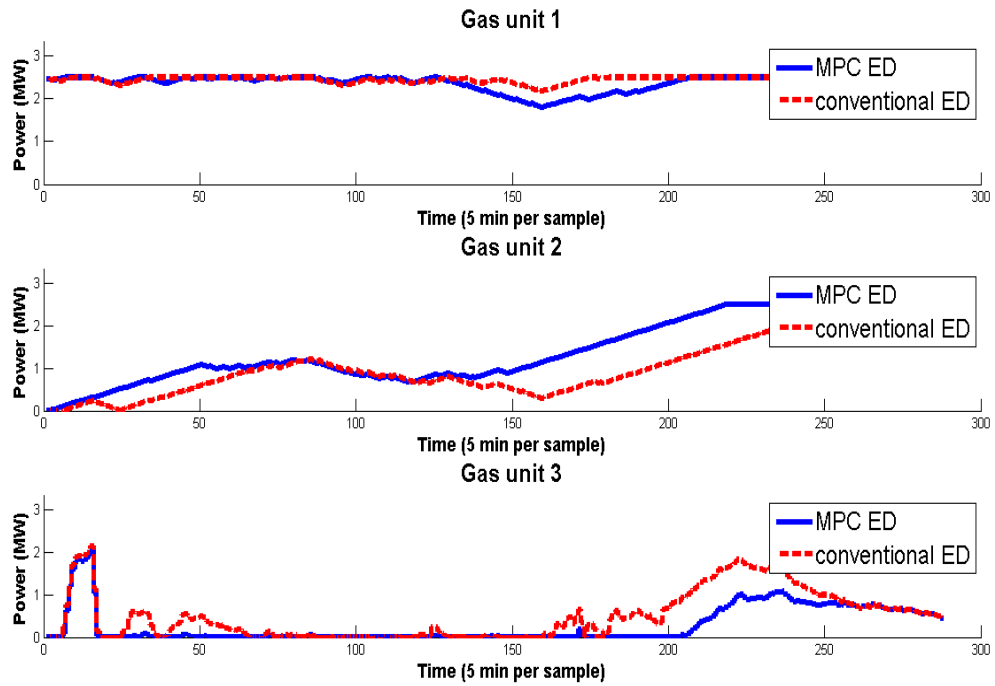
Table 6.3 shows the result of the different scenarios were the ramp rate limits has all fast responsive units. It is important to notice that from the set of 5 days of simulation all of them present the same behavior in which the performance of the conventional dispatch as well as the predictive dispatch is the same.

The simulation result shows that there is no difference between the conventional and the predictive dispatch because the fast response capacity of the gas units allows them to follow even the high variations of the renewable energy sources at least cost. For example in Fig.6.2a it is shown that the conventional generation dispatch solution is mostly the same as the optimal solution found with the predictivbe strategy in the previous scenario (See Fig.6.1a) and in this case is achieved with both control strategies.

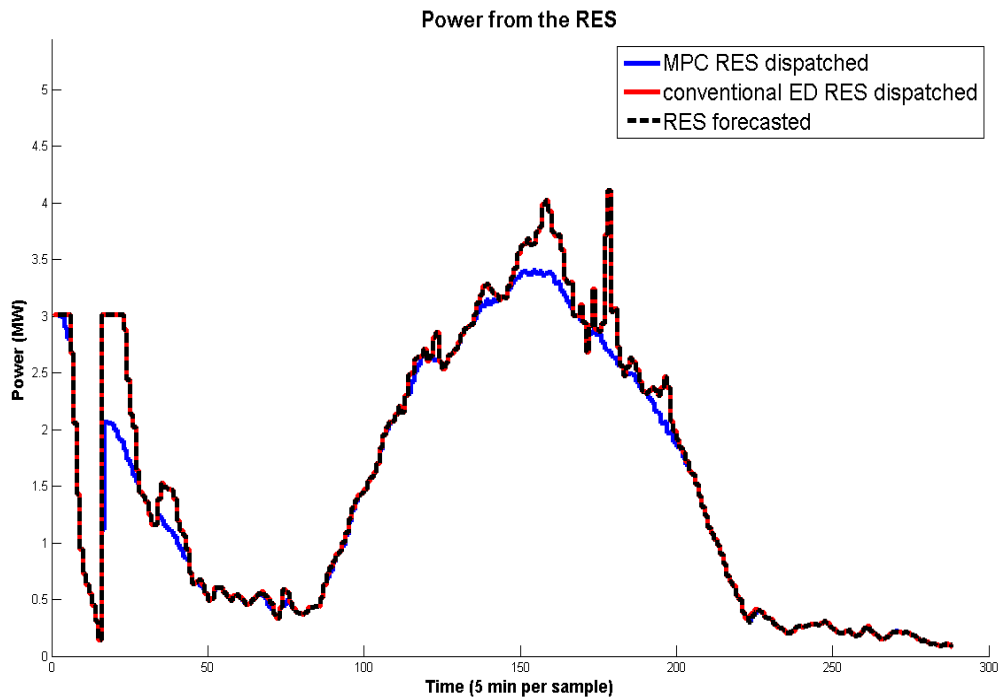
In this simulation scenario, given the forecast error the second controll strategie is active and the result is shown in Fig.6.4a and Fig.6.4b. It can be appreciated that for this simulation the renewable energy sources express a very little variability, then the forecast error is mininum but the goal target of eliminate the forecast error is accomplished.

Sim	Forecast	MPC cost (USD)	Conv cost (USD)	MPC cost benefit (%)
2	no	2.97E5	2.97E5	≈ 0
	yes	2.977E5	2.977E5	≈ 0
4	no	2.993E5	2.993E5	≈ 0
	yes	2.992E5	2.992E5	≈ 0
6	no	2.947E5	2.947E5	≈ 0
	yes	2.949E5	2.949E5	≈ 0
8	no	2.935E5	2.935E5	≈ 0
	yes	2.935E5	2.935E5	≈ 0
10	no	2.962E5	2.962E5	≈ 0
	yes	2.963E5	2.963E5	≈ 0

Table 6.3 Result for fast ramp rate simulations

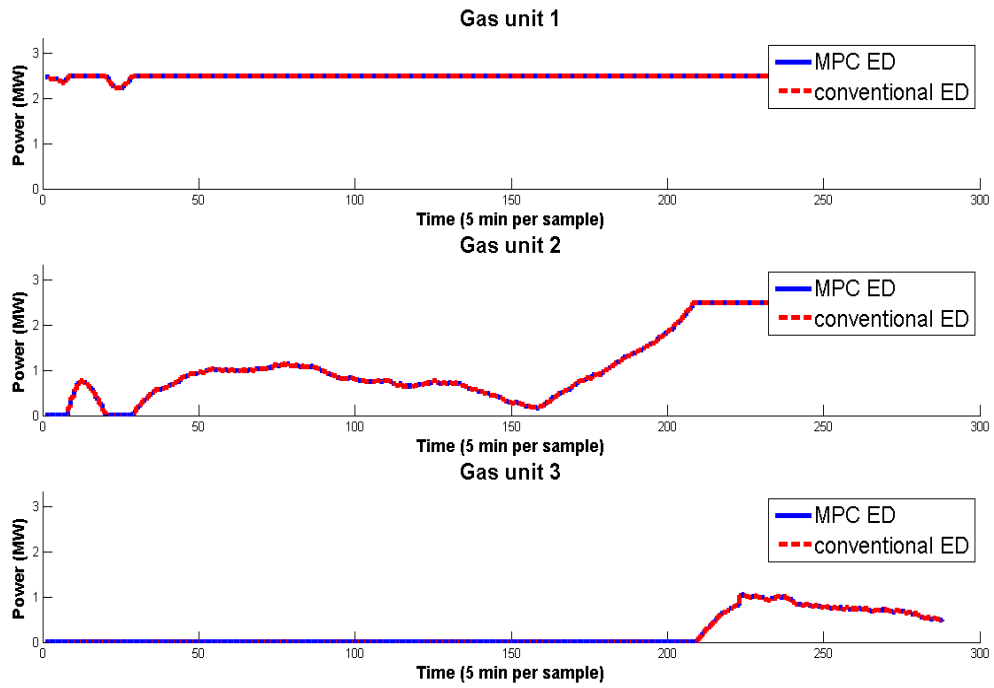


(a) Gas generators result

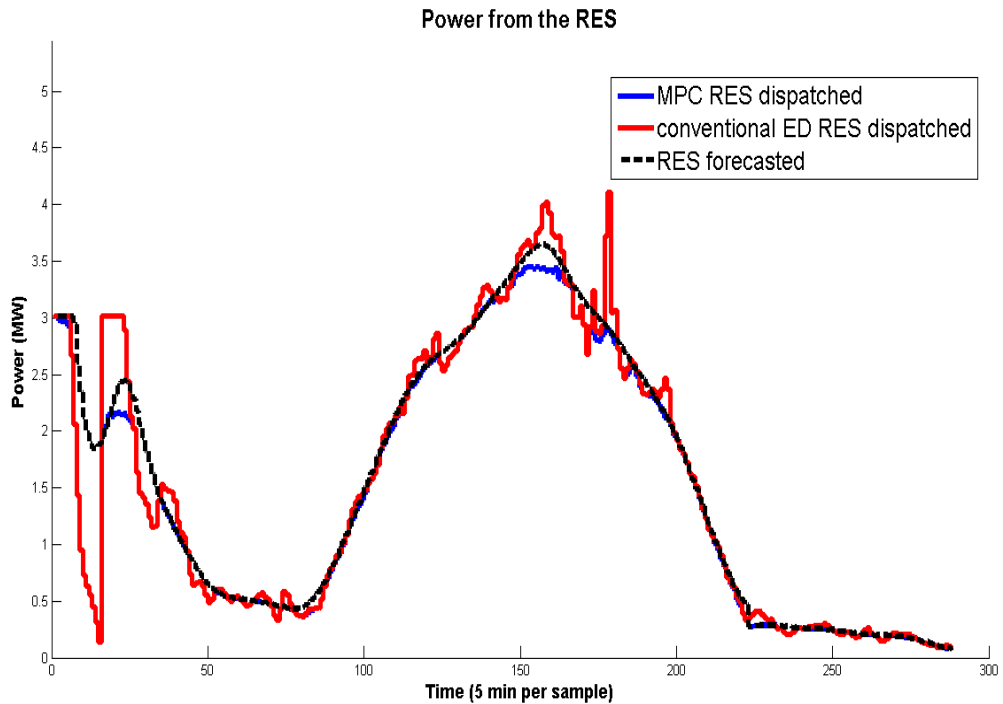


(b) Renewable energy source result

Figure 6.1 May 8 simulation result without forecast



(a) Gas generators result



(b) Renewable energy source result

Figure 6.2 May 8 simulation result with forecast power generation

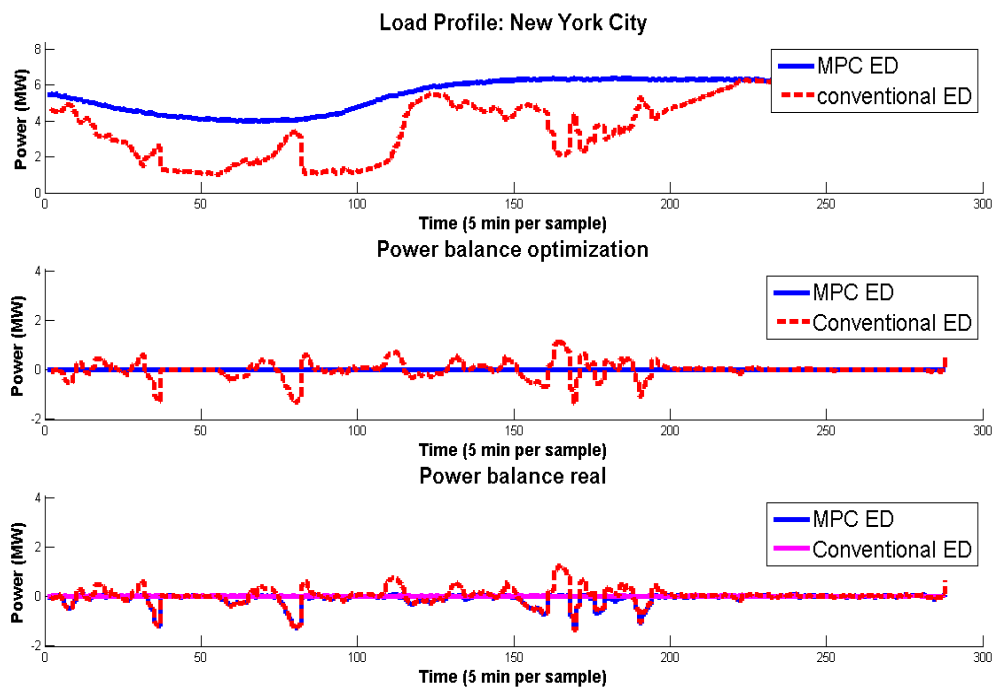
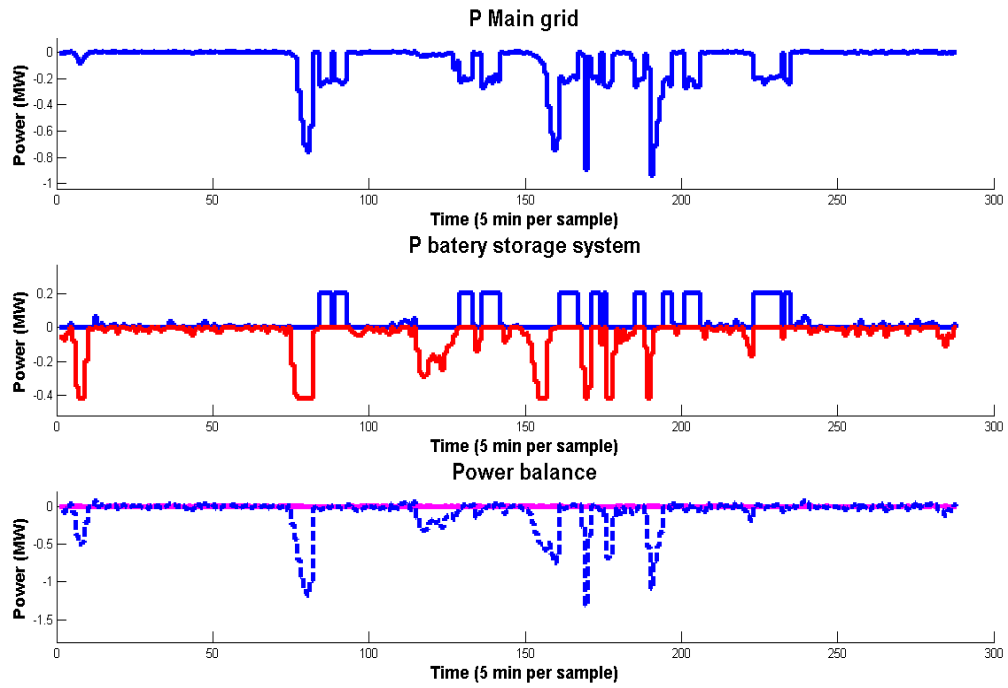
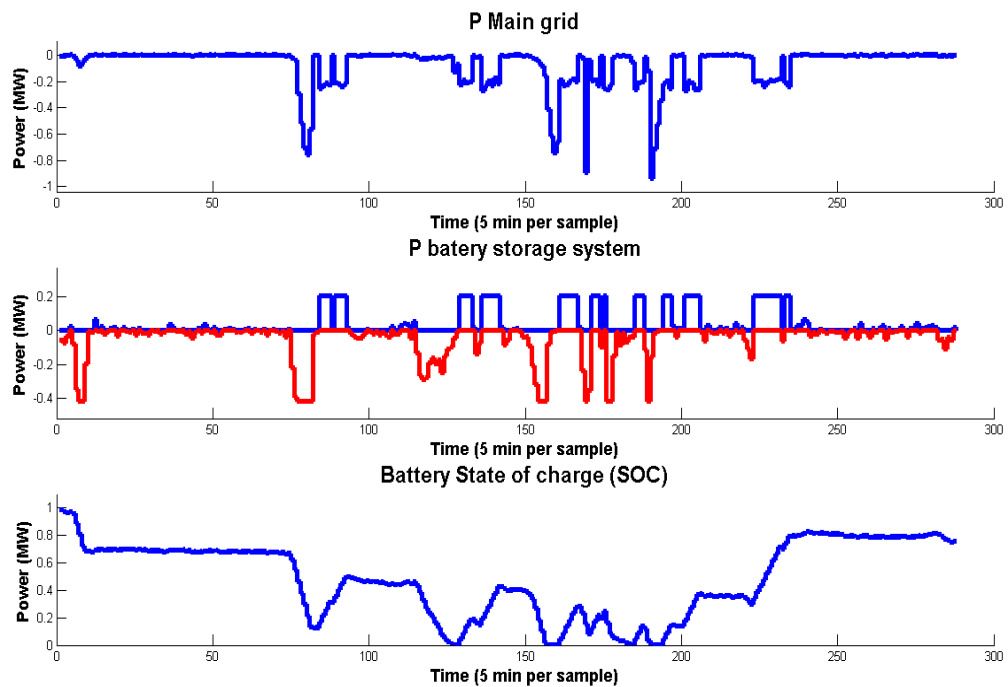


Figure 6.3 May 8 simulation result with forecast, load profile and power balance error



(a) Main grid, battery storage system and power balance error



(b) battery storage system SOC result

Figure 6.4 May 8 simulation result with forecast of the storage systems

Chapter 7

Conclusions

This work presents two ways to develop the economic dispatch problem of a microgrid in the presence of renewable energy sources based on the conventional static optimization procedure and a dynamic predictive strategy. Contrary to the idea of defining the intermittent resources as non-dispatchable units, the proposed method shows that it is desirable to control them and treat as dispatchable units when the generation portfolio includes cheap and slow units. By doing this, the MPC can handle the high variations on the renewable sources output without using large amount of power from expensive generators. It is shown also, that for today's power systems scenario there are no significant differences between both algorithms but as the renewable sources penetration level increases the conventional dispatch has the worst result compared to the benchmark where no intermittent sources are considered. On the other hand the MPC approach yields to lower the generation cost of the microgrid for all the penetration levels and demonstrates that it has a great potential for such systems.

For the forecast scenario the renewable energy sources signal produced by the forecast methodology results in a smoothed signal similar to the renewable energy sources dispatched by with the predictive strategy when there is no forecast. This means that indirectly the forecasted signal is doing a pre-allocation of the renewable sources so that the predictive dispatch does not have the chance to improve the dispatch of those units.

Furthermore three principal extensions to the analysis need to be considered in future work. First, the study and development of hybrid storage systems which allows to improve the dispatch of the renewable energy sources. The idea behind the predictive dispatch is to use fast responsive storage systems e.g. ultra capacitors or for the second controller proposed and traditional storage systems as controlled dispatchable units that would be included in the model predictive dispatch control. Second, it would be interesting to include control capabilities in the consumption side which means demand response programs. In this way the first study that can be performed is to include electric vehicles as dynamically responsive load, this could be another alternative to deal with the power balance error. Finally, in future grid connected microgrids it is expected to be performed an active exchange with the main grid not only for the forecast error balance but also for dispatch purposes. In this direction new economic market must be designed to regulate those interactions between main grid and different grid connected microgrids.

Chapter 8

Appendix

8.1 Appendix A: Variability of renewable resources

In order to quantify the variability effects of the RES, wind speed and global horizontal irradiance were classified in terms of the magnitude and frequency of high ramp events. The comparison is made between a 5 minute and 1 hour sampling time.

8.1.1 Real Data

First, a set of empirical data from different national renewable energy laboratory (NREL) stations located over the United States were selected (see Figure 8.1). The information collected corresponds to wind speed measured at 100 m above the ground and global horizontal irradiance. Because the wind speeds are not always measured at 100 m in all the stations, e.g. (8.1) serves to scale all the wind speed values for the equivalent heights. U and U_r are the desired and reference wind speed (m/s), z and z_r (m) are the desired and reference height and α corresponds to a constant that is typically defined equal to $1/7$. A wind turbine Vestas V90-3.0MW was used as reference for the wind generator and for the photovoltaic field a simple calculation based on the PV field area gets the desired rated power.

$$U = U_r(z/z_r)^\alpha \quad (8.1)$$

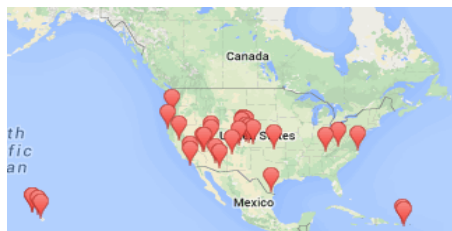


Figure 8.1 Different NREL stations located over the United States

- Arizona station:** Comparing the data corresponding to the wind speed at a 5 minute vs 1 hour sampling interval, it can be said that the hourly measurements filter the data, smoothing out most of the wind speed peaks that happen in the intra-hour time as it is shown in Figure 8.2. This situation implies that the power output of the wind generator will differ considerably between both sampling time selected since the power generation is a quadratic function of the wind speed. Thus the dispatched power scheduled based on 1 hour sampling data will produce a significant error during the intra-hour period.

The difference in ramp events between the 5 minute and 1 hour sampling intervals are evident. Figure 8.2 shows that the ramp events of the 5 min sampled data are much higher than the ramp events of the 1 hour sampled data, specially for the first eight months. For example, in the whole year, the maximum ramp events greater or equal to 30% from the 1 hour data appear only 3 times in one day, in contrast to the 5 minute data those ramping events in June happen 20 times in one day. If most of the ramp events greater than 30%, which can be considered dangerous for the power system operation happen during the intra-hour period, the system operated at a 1 hour sampling interval has to overcome impact of those event only with the reserve capacity. That carries a high economical and operational risk.

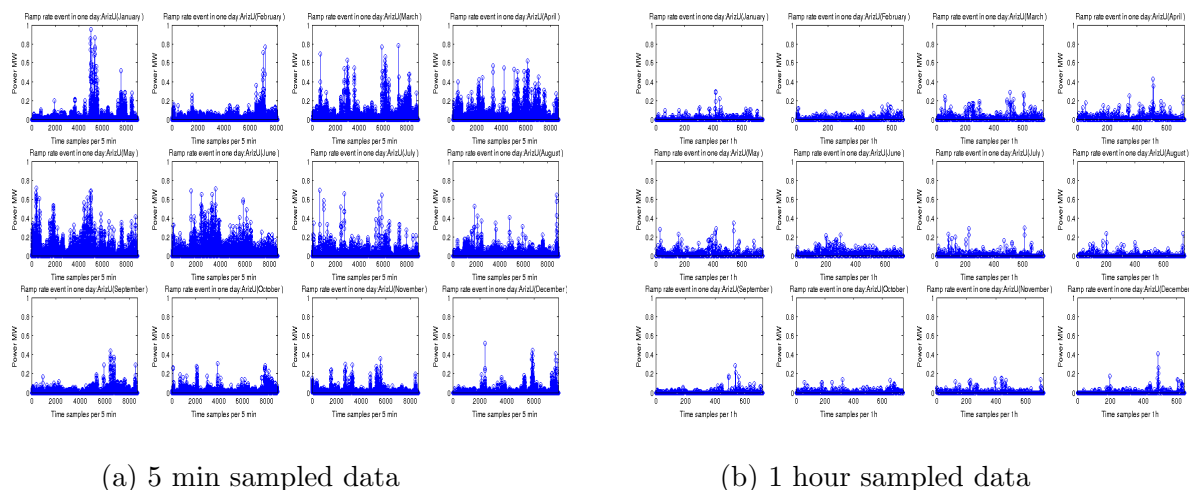


Figure 8.2 Ramp rate wind speed events of Arizona station

Figure 8.3 shows the global horizontal irradiance ramp events with significant differences between the 5 minute and 1 hour sampling time. Within the 1 hour data the same pattern can be appreciated for all the months having an average per of 20% of ramp rate, additionally the ramp events never cross 50% of the installed capacity. In contrast, the 5 minute data shows different patterns of the ramping events by months and present a high variation with ramp events from 40% up to 70% of the installed capacity mainly during the summer. The numerical results show that the maximum ramp events greater than 30% in one day with the 1 hour data occur at most 9 times in August, while in

the 5 minute data there are found 33 times in July. The high variability of the global horizontal irradiance when it is sampled at 5 minutes suggest that it is important to consider the dispatch of the PV generation at this sampling rate in order to handle those high ramp events that are committed with the 1 hour sampled data.

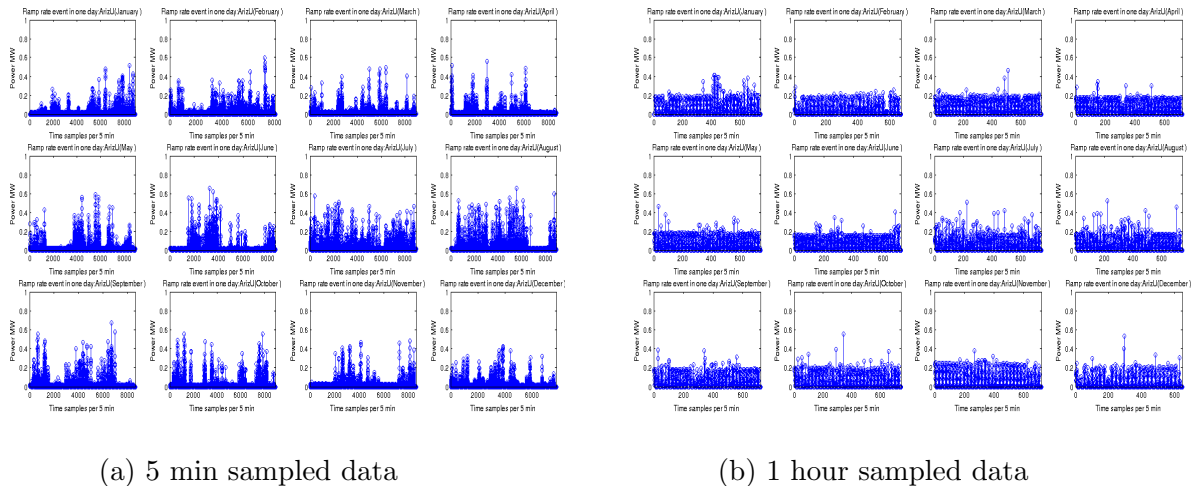


Figure 8.3 Ramp rate global horizontal irradiance events of Arizona station

To sum up, the difference between both sampling time data, is the fact that the power delivered by the RES generators at 5 minute basis are greater than the 1 hour, so that the dispatch of these generators always will have an offset which will impose difficulties to determine the reserve capacity and the dispatch of other generators. An economic dispatch performed every hour will suffer of security problems given the difficulty to guarantee the power balance during the intra-hour period.

8.1.2 Simulated Data

Given the difficulty to obtain real data from the renewable sources at different locations so as to perform the analysis of the variability of wind speed and solar irradiance, the set of simulated data developed by the NREL organization was used. The NREL creates a simulated data on wind speed and solar irradiance as part of the study of renewable source integration for the United States. The wind speed data were made based on weather information and numerical weather predictions and in terms of PV production the irradiance was generated using a sub-hour irradiance algorithm that estimates the irradiance based on satellite images and calculate, the PV production from a field of $40 \text{ MW}/\text{km}^2$.

For this variability study, five different locations on the west coast, including the state of California, Colorado, Utah, Texas, and Oregon were used to analyze the characteristic of variability of the renewable sources e.g. wind and solar. The wind generator used to calculate the power output from wind source was a Vestas V90-3.0MW wind turbine. The PV field had a rated power varying from 52 MW at California, up to 118 MW in Utah.

- **California:**

According to the frequency and magnitude of the wind speed ramping events the results presented in Figure 8.4 shows that there exist some outliers of very high ramp events in the 5 minute case which are not present in the 1 hour simulations, but contrary to the previous real data results, with the simulated data the ramp rate events are considerably greater in the 1 hour scenario.

The results presented in Figure 8.4, illustrate that the behavior of the wind speed ramping events in the simulated data scenario are not significant. Given the low variability of the wind speed here, it can be said that the economic dispatch are able to handle easily the variations during the intra-hour period. Then the dispatch performed with the 5 minute sampling interval is not necessary.

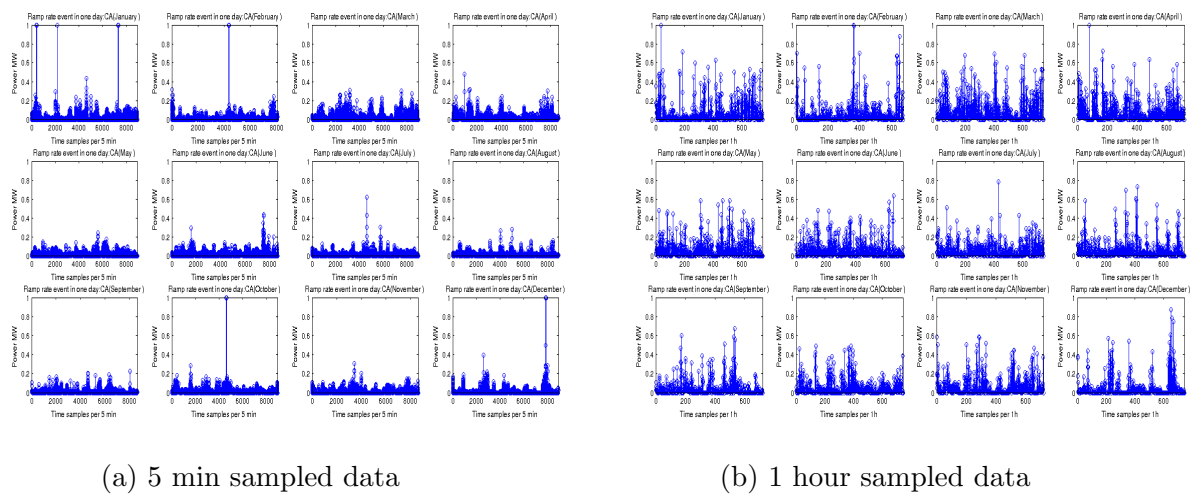


Figure 8.4 Wind speed ramp rate results, for California.

In terms of PV production variability (which is a consequence of the irradiance variability) the data obtained from the California location shows that the ramp rate events with the 5 minute case is very low in terms of magnitude most of the year. Only the months of March and April have some significant ramp events greater than 30% during the whole month. In contrast, in the months of August and September the variability of the PV production stayed below 20% most of the time (See Figure 8.5).

Comparing the maximum ramp events that happen in one day of 5 minutes and 1 hour data it can be said that the 5 minute results overcome the one hour scenario. Taking into account that for some specific months like April, the high ramp events greater than 30% are four times the ones happen in the 1 hour data and its unpredictable nature, the 5 minute sampling interval can be considered for the economic dispatch in order to prevent security concerns.

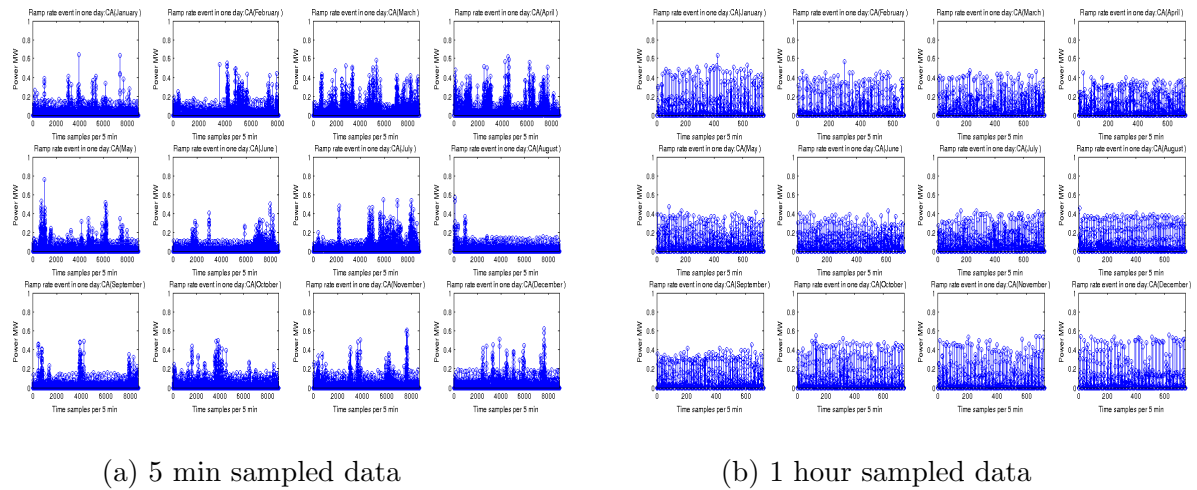


Figure 8.5 PV field generation ramp rate results, for California

The fact that the wind speed simulated data ramping events are greater for the 1 hour scenario, allows to say that if the wind speeds are higher it is difficult to change abruptly its value in short periods of time (e.g. minutes), so the variance in the intra-hour is negligible for security and dispatch purposes. Additionally, the poor result of the maximum ramp events occurrences in one day especially for the 5 minute case, confirm that the simulated data does not contribute with significant variability at that sampling rate, contrary to the results found in the experimental data where the variability of the intra-hour period is high. That characteristic allows to stated that the economic dispatch of microgrids that have only wind resources and conventional generation should consider adopting the 5 minute sampling interval only for locations with similar behavior as the one of the NREL stations.

In terms of the global horizontal irradiance variability the result shows more similarities than differences when comparing the empirical data with the simulated modeled information. In both scenarios the irradiance behavior presents some important variability when the data is being sampled at 5 minutes. Even if the radiation patterns seem to be much more constant than the wind speed, there are days in which the number of ramping events greater that the 30% of the installed capacity rose 30 times in one day for the most variable months. Those ramping events during the intra-hour period can lead to power balance problems as well as economic inefficiencies, so that, it would be desirable to include the 5 minute sampling time in the economic dispatch of microgrids with PV generation at high penetration levels.

The conclusions of the wind speed and the irradiance (or PV field power production) analyzed can be summarized as follows:

- The empirical data taken from the NREL measurement stations provide a variable behavior of the resources, but a low quantity of them, especially the wind speed. This allows to conclude that even if the pattern of the data is interesting for the economic dispatch study, those stations are poor locations to install renewable energy sources.
- Simulated data presents the contrary situation to the data from NREL stations, the different locations show much more amount of renewable sources during the whole year,

but the variability of the wind speed is considerably lower, so they are good examples to install renewable sources but the ramping events do not happen frequently.

8.2 Appendix B: Renewable energy sources forecast

When the economic dispatch deals with renewable energy sources one of the most important task is the forecast of the data. As it was mentioned before the solar irradiance and the wind speed are climate variables which have an unpredictable behavior, characterize with high variability. Fig.8.6 and Fig.8.7 shows a typical behavior of both solar power and wind speed data, the solar power data has a more stable pattern along the different days. Contrary the wind speed data shows different days where from one day to the other the difference in the availability can be more than the 80% which means that the consecutive days do not have always the same availability.

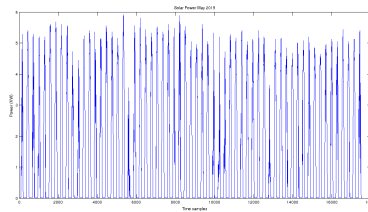


Figure 8.6 Solar power data

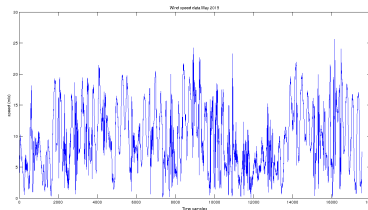


Figure 8.7 Wind speed data

8.2.1 Forecast methodology

Given that the forecast of the solar and wind data produce a very poor results whit forecast fit of the validate data less than 30%, a different methodology was purposed. Taking into account that the wheater data has diferent periodic patterns such as weekly, dayly and for example in the case of the solar irradiance hourly correlation with previous days, the original wind speed and data power pass through a signal process in order to performe the corresponding forecast.

To illustrate the process in Fig.8.8 is the block diagram of the forecast procedure developed in this project. First the original signal e.g wind speed pass through a filter stage were two differnt filter signal result from the process. The idea behind filter the original data is to smoothing the signal in order to capture the low frecuency dynamic of the signal which has more periodic patterns and is easier to model. The sampling frecuency is determined equal to the sampling frecuency of the economic dispatch which is 5 minuts, the filters were designed using low pass FIR filters with hamming window in the filter design tool box of matlab.

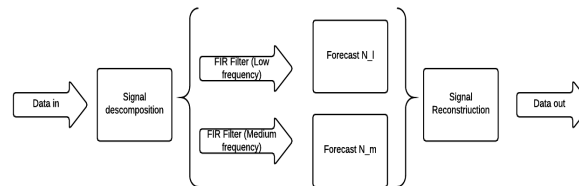


Figure 8.8 Porpuse forecast metodology block diagram

Then, each of the two filter signals need to be forecasted, then using the identification tool box the matlab different polynomial process were tested. After develop several simulations the model selected for the different filtered signal is an autoregressive model (ARX) using 72 coefficients. Each signal produces an fit model that ranges between 60% to 80%. Finally in order to produce the forecast of the original signal a signal reconstruction is made. In the signal reconstruction proces the output signal is composed by merge the first 24 steps of one filter data with the rest of the other signal data. By doing this procedure the forecast of the signal corresponds to a smoothed signal of the original data but achieve a better performance from the prediction of the original data.

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