Operational planning and optimization for fuel consumption minimization of a microgrid comprising PV-based active generators

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Abstract: This paper presents a medium and long-term operational planning optimization of a microgrid comprising renewable energy-based active generators. The problem of unit commitment is solved by the approach of dynamic programming with the objective of minimizing the fuel consumed by conventional generators. The studied microgrid comprises PV-based active generators with embedded storage and three micro gas turbines. Based on forecasts of the energy available from the PV generators, the storage availability and the power demanded to supply the loads in autonomous mode, the presented algorithm elaborates the 24 hour-ahead operational planning. In function of deviations from the forecasted values and taking into account actual forecasts, the presented medium term energy management adjusts the operational planning.

Keywords: microgrid, smart grid, optimization, cost, reduction, renewable energy, photovoltaic generators

1. INTRODUCTION

One of the main drawbacks of Renewable Energy-Based Generators (REBG) is the fluctuations of their output power, depending on the primary source (such as the sun, wind etc.). Increasing the REBG penetration ratio in electric distribution systems could cause difficulties for system operators in matching the power production and demand thus degrading the quality of power supplied to the customers. Thus, meeting future problems with the conventional grid control architecture or simply reinforcing the current grid are not optimal solutions. A modern power system should take advantage of new communication and forecasting technologies and interactively integrate the behaviour of all users and producers connected to it (Xinghuo, Y. et al., 2011). The future Smart Grid (SG) organization has to incorporate distributed intelligence at all levels of the electric network in order to improve efficiency, reliability and security (Li. F., Hamidi. V., 2010). The smart grid will be formed by microgrids interacting and operating in parallel (Sinuskthavorn et al., 2010)(fig.1).

One of the problems to overcome is matching power demand and production in an optimal way and minimizing the usage of non-renewable resources for electric power production. A first solution to this problem is the concept of PV-based Active Generator (AG). It integrates a photovoltaic array with batteries and supercapacitors for long and short term energy storage (Lu et al., 2011). Another part of the solution is to integrate locally REBG, conventional generators and loads in clusters called microgrids. They are then aggregated and controlled by a Microgrid Central Energy Management System (MCEMS) in the overall electrical distribution system (fig.1). The MCEMS itself could perform optimization of the 24 hour-ahead local operational planning of energy sources and communicates with the Distribution System Operator (DSO) thus facilitating large-scale power plants dispatching and increasing overall efficiency (El Bakari, 2010, Schmitt, 2010, Brown, 2008). By this way, energy from REBG is consumed or stored locally in the cluster, thus losses due to energy transmission can be neglected.

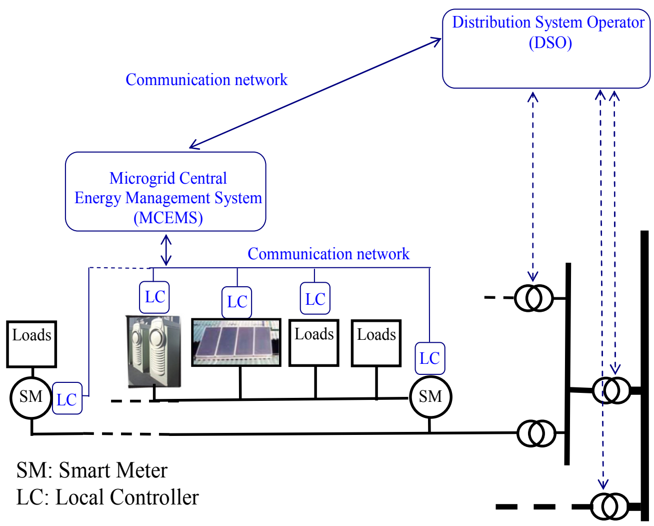

Fig.1. Framework of the MCEMS for microgrid control and communication with DSO

In our previous works the organization of a MCEMS and, the integration of PV-based generators have been studied (Lu and Francois, 2009). A multi-objective optimization for long term operational planning in order to reduce the three main pollutant emissions of the micro gas turbines (CO_2, CO and NOx) has been implemented in the studied system (Kanchev et al., 2010). By using this algorithm, a 9% reduction of CO_2 equivalent emissions over a 24 hour operational planning has been achieved.

Further, a long term energy management optimization algorithm has been implemented, using the approach of unit commitment by dynamic programming with the objective of minimizing the CO_2 equivalent emissions (Kanchev, Francois and Lazarov, 2011).

In this paper, the medium and long-term operational planning of a microgrid including PV-based AG and micro gas turbines is presented. The objective function is to minimize the consumed fuel by conventional generators in the system. The proposed solution is validated by simulations in Matlab/Simulink.

2. ORGANISATION OF THE MCEMS

In order to create a 24 hour-ahead operational planning, these calculations have to be done for all time steps. The goals of the MCEMS algorithm are:

- to use the maximum of the REBG energy,
- to minimize the CO_2 equivalent emissions of the gas turbines by setting their power references such, that they produce the minimum pollution and they have minimum start up and shutdowns.

Many difficulties arise. First, the REBG power meets rarely the power request from the MCEMS, moreover this power is not constant during the whole 24 hour-ahead optimization period. Moreover, there are numerous strategies for managing multiple gas turbines as auxiliary power sources for supplying loads (as example, a strategy may be to use the MGTs having the highest maximum power output as a priority source). Finally, other constraints exist to drive a gas turbine as the minimum power set point, the response time …

The MCEMS must assign power references and also other appropriate control signals to the DER units, conventional production units and controllable loads (Katiarei et al., 2008). The microgrid management is analyzed through various functions that can be classified in a timing scale presented in fig. 2.

The long-term energy management elaborates a 24 hour-ahead operational planning including:

- the "REBG production forecast" including the time dependency of the prime source, environmental impacts and cost of generation,
- the management of non-sensitive loads that may be disconnected/shed according to the supervision requirement,
- the provision of an appropriate level of power reserve capacity according to the electricity market and the load demand forecast,
- the maintenance intervals.

The medium-term energy management includes:

- the adjustment of forecasts for the power available from REBG and power demanded by the loads,
- the adjustment of the long-term operational planning, based on deviations in the above mentioned forecasts from those predicted 24 hour-ahead.

The short-term power balancing is performed in the local controllers of generators and includes the RMS voltage regulation and the primary frequency control (Li et al., 2009).

The long term operation schedule and the energy management can be mathematically expressed and results to an Unit Commitment Problem (UCP). It can be solved by means of many optimization algorithms. Due to the complexity of the problem, the computational time may vary according to different optimization approaches such as: dynamic programming, ant colony optimization, genetic algorithm, exhaustive enumeration, taboo search and others. In this study the unit commitment problem is considered to minimize the consumed fuel within a microgrid and is solved with the dynamic programming approach.

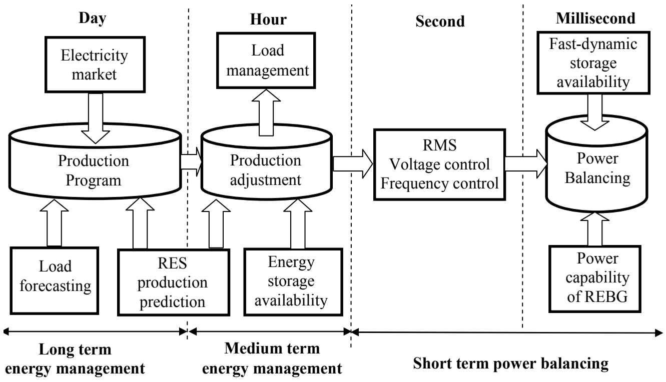

Fig. 2. Timing classification of control functions for MCEMS

3. CONTROL OF THE ACTIVE GENERATORS AND THE MICRO GAS TURBINES IN THE MEDIUM TERM

3.1. *The concept of Active Generator.*

One of the main drawbacks of actual photovoltaic generators is that the output power fluctuates and depends on weather conditions. Moreover these generators are only capable of delivering the maximum available power. Hence more power than required may be generated and so may induce grid instabilities. Currently experiences show that the maximum penetration ratio of these passive PV generators in European networks is limited to about 30%.

One way to increase the penetration ratio is to upgrade actual PV generators in order to transform them into controllable, dispatchable generators. These active generators offer new flexibilities for the grid system operators and consumers. Considered AG's contain batteries for long term energy reserve availability and ultra capacitors for short term power regulation (fig. 3). Thanks to these embedded storage technologies and the dedicated control system, this generator is capable of delivering prescribed power and power system services to the microgrid although it is limited to the energy stored in the batteries (Lu et al., 2011).

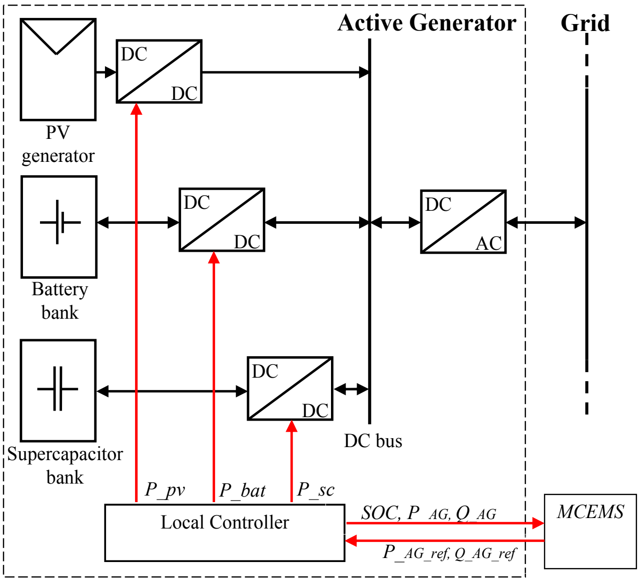

Fig. 3: Scheme of an Active Generator including short and long term energy storage

3.2. Microgrid Medium-term control

The AG is capable of maintaining a prescribed power reference, received from the MCEMS, in the limits imposed by the actual State Of Charge (SOC) of the batteries. According to daily predictions of the available power and energy from the PV ($\widetilde{P}_{PV\_24h}$) and the required power and energy of the loads ($\widetilde{P}_{Load\_24h}$), a power production planning for the AG and for the micro turbines is determined by the MCEMS. The central energy management system refreshes the power references each 30 minutes. If the available PV power is greater than the power demanded by the MCEMS, the excess is stored in the batteries. When no PV power is available, power stored locally in the batteries can be used to satisfy the power request if their SOC is sufficient for this.

Power references from the long-term energy management are calculated by the MCEMS with a 24-hour ahead planning from the load and PV production forecasting. Sometimes the real situation (weather conditions, power demand by loads) are different from the forecasted conditions. Current forecasting techniques allow us to have an updated forecast every 30 minutes. In practice, we consider the current forecasted loads ($\widetilde{P}_{Load\_t+1}$) and forecasted PV production ($\widetilde{P}_{PV\_t+1}$) for the next half of an hour (time step *t+1*). The deviation from the 24h-ahead forecasted data is expressed as:

$$\Delta P_{PV\_t+1} = \widetilde{P}_{PV\_24h(t+1)} - \widetilde{P}_{PV\_t+1} \quad (1)$$

$$\Delta P_{Load\_t+1} = \widetilde{P}_{Load\_24h(t+1)} - \widetilde{P}_{Load\_t+1} \quad (2)$$

Where $\widetilde{P}_{PV\_24h(t+1)}$ and $\widetilde{P}_{Load\_24h(t+1)}$ are the 24-ahead forecasted values of P_{Load} and P_{PV} for time step (*t+1*), ΔP_{PV_t+1} and ΔP_{Load_t+1} are the deviations from the forecasted values.

The medium-term energy management takes into account these deviations by modifying power references of the generators according to the new situation. This operating is similar to the secondary control in large power systems. Here the refreshing of power references for the active generator is done each half of an hour by the MCEMS by adding the deviation in available PV power (ΔP_{PV_t+1}) to the power reference calculated 24 hours ahead:

$$P_{AG\_ref\_t+1} = \widetilde{P}_{AG\_ref\_24h\_t+1} + \Delta P_{PV\_t+1} \quad (3)$$

Where $\widetilde{P}_{AG\_ref\_24h\_t+1}$ is the AG power reference, calculated by the MCEMS 24 hour-ahead. A correction in power references for the micro gas turbines in the system is then induced. Normally the power that has to be delivered by the MGT's (the residual load) for every 30-minute time step is $\widetilde{P}_{Load\_R\_24h\_t+1}$. When deviations in $P_{AG\_ref\_t+1}$ or P_{Load_t+1} occur, a new set point of the residual load is calculated:

$$P_{Load\_R\_t+1} = \widetilde{P}_{Load\_R\_24h\_t+1} + \Delta P_{Load\_t+1} - P_{AG\_ref\_t+1} \quad (4)$$

This power has to be delivered by the Micro Gas Turbines (or other conventional sources) in the system, following the algorithm presented in our previous studies (Kanchev, Francois and Lazarov, 2011). In the algorithm, a 10% reserve in MGT's power references is scheduled, so if the deviation in $\widetilde{P}_{Load\_24h\_R\_t+1}$ is less than 10%, corrections in MGT power references can be handled by the local controllers. In other words, if inequality (5) is true, power references for time step *(t+1)* are recalculated by the local controllers and integrated in the MGTs:

$$\left| \frac{P_{Load\_R\_t+1} - \widetilde{P}_{Load\_24h\_R\_t+1}}{\widetilde{P}_{Load\_R\_24h\_t+1}} \right| \leq 0{,}1 \quad (5)$$

If the inequality (5) is not true, power references for (*t+1*) have to be recalculated by the medium term energy management. The medium term control algorithm is presented on fig. 4.

4. LONG TERM ENERGY MANAGEMENT

4.1. Formulation of the Unit Commitment Problem.

UCP is based on the expression of an objective mathematical function to determine the operation schedule and cost reduction in large power systems. The operation schedule consists in selecting generating units to be used and when they should be committed. The general objective of unit commitment is to minimize the system total operating cost while satisfying all of the system constraints (Longethiran, 2010). As the power industry goes restructuring, the UCP could be considered and extended to small DG clusters. To do this, some simplifications are allowed: the minimum unit ramping and unit fuel constraints are not taken into account and also transmission losses in the microgrid are neglected.

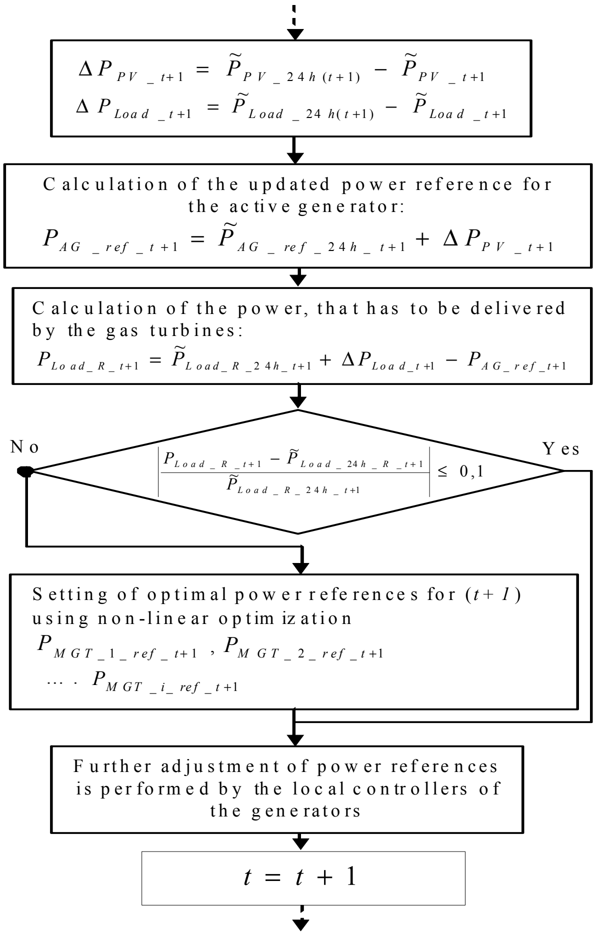

Fig. 4. Medium-term control of a microgrid

The cost function of each generator is expressed as a non linear function of its power output $C_i(P_{MGT\_i}(t))$. Penalties for start-up and shutdown of the units are applied. The start-up and shutdown penalties for each unit are expressed by the function $C_{pe\_i}(\delta_i(t),t)$. δ_i is the state of each generating unit during each time period (1 if the unit is running or 0 if the unit is shut down). The penalty function adds an amount of penalty cost (start-up penalty) if the unit is actually off and will be started in the next period. In the same way a shutdown penalty is applied if the unit is committed and will be stopped in the next time step. Start-up penalty is considered equal to the cost of consumed fuel during 5 minutes operation at full load. Shutdown penalty is considered equal to the cost during 2.5 minutes operation at full load.

The 24 hour-ahead operational planning is discretized in 48 steps (t) of 30 minutes (τ). Power references remain constant during each step. The short-term power balancing functions in the LC of generators performs the real-time power balancing (Lu et al., 2009, 2011, Li et al., 2009, Katiarei et al., 2008). The objective function is:

$$S(t) = \sum_{i=1}^{3} (\delta_i(t).C_i(P_{MGT\_i}(t),t) + C_{pe\_i}(\delta_i(t),t) \qquad (6)$$

$P_{MGT\_i}(t)$ is the generated power, which varies at each time step t. i is the unit number (in our studied system there are 3 micro gas turbines).

The objective function for the whole system is to minimize the total fuel consumption of a 24 hour operation:

$$f = \sum_{t=1}^{48} S(t) \qquad (7)$$

With N active generators and M micro gas turbines, the power production must be shared among the DER units in order to meet the loads power demand. In each discrete time step the power balancing between the loads (P_{LOAD}) and the generators (P_{AG_i} and P_{MGT_i}) must be performed by the MCEMS with a maximum use of the "green" PV energy:

$$P_{LOAD}(t) = \sum_{i=1}^{N} P_{AG\_i}(t) + \sum_{i=1}^{M} P_{MGT\_i}(t) \qquad (8)$$

The constraints include also the micro gas turbine loading level, which has to be more than 50% of the MGT's rated power for improving efficiency:

$$P_{MGT\_i} \in [0.5,1] P_{MGT\_i\_\max} \qquad (9)$$

The third group of constraints refers to the microgrid operation mode. The constraints differ from one mode of operation to another (PV power available or not, active generator's battery state of charge) and are detailed in our previous works (Lu et al., 2009, 2011). The real and reactive power production must be shared among the DER units (active generators) and the gas microturbines.

4.2. The Dynamic Programming approach to solve the unit commitment problem.

There are several approaches to implement an optimization procedure. One approach is an exact mathematical optimization procedure called "dynamic programming". Dynamic programming is a method for solving problems that exhibit the properties of overlapping sub problems and optimal substructure. In some cases this method takes much less computing time than other methods.

The term was originally used in the middle of the 20th century by Richard Bellman to describe the process of solving problems where one needs to find the best decisions one after another. The Bellman equation restates an optimization problem in recursive form. The solution of Bellman's recursive equation (also known as a dynamic programming equation) (10) for all of the time steps is the optimal solution of the problem. Optimal solutions of these subproblems are used to find the optimal solution of the overall problem by recursion, as presented on fig. 5.

Recently the dynamic programming principles have been applied to solve the unit commitment problem in large power systems (Longethiran, 2010). In this study, the objective is the determination of the number of units committed and their power references to supply the loads for every time step in the operational schedule of a microgrid. An example is presented on fig.5. In order to satisfy a given power demand at time step *t,* numerous combinations of committed generators and power references: $S_1(t), S_2(t)...S_n(t)$. The optimal trajectory or optimal path) is the one that minimizes the objective function $f = \sum_{t=1}^{48} S(t)$ for all the 48 time steps while satisfying the power demand and all other constraints. All sub problems (6) are solved in advance and then are used to build up the optimal solution of the main problem (10).

Solving the general problem recursively is of crucial importance, because, when starting from the first time step, the first suboptimal solution will not always lead to a global optimal path to the final time step. In general, a problem can be solved with optimal substructure using a three-step process:

1. Break the problem into smaller sub problems.

2. Solve these problems optimally using recursion (10).

3. Use these optimal solutions to construct an optimal solution for the original problem.

The sub problems are, themselves, solved by dividing them into sub-sub problems, and so on, until a case is enough simple to be solved in a constant time.

The optimality principle says that the optimal trajectory is the one that minimizes the objective function with regard of the resulting steps, starting backwards from the final state. So, for our problem, the objective function is expressed as:

$$F(S(t)) = \min\{S(t) + F(S(t+1))\} \quad (10)$$

$F(S(t+1))$ is the suboptimum function for the $S(t+1)$ time step, $S(t)$ is the cost (equation 6).

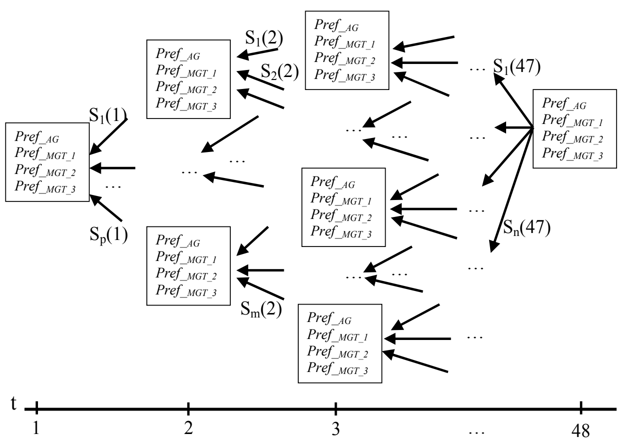

Fig. 5: Illustration of the principle of optimal path by dynamic programming

3. ASSESSMENT OF MICRO GAS TURBINE FUEL CONSUMPTION

Micro Gas Turbines are well suited for distributed generation applications due to their flexibility in connection methods, fast dynamic response and emission profile, compared to diesel groups.

The energetic efficiency between thermal energy and electric energy is defined as:

$$\eta_i(t) = \frac{E_{MGT\_i}(t)}{F_{MGT\_i}(t)} \quad (11)$$

Where F_{MGT_i} ($kWh_{thermal}$) is the fuel thermal energy supplied to the gas turbine combustion chamber in order to have at the generator side the useful electric energy output E_{MGT_i} ($kWh_{electric}$). This efficiency is not linear in function of the partial load characteristics (fig. 6). In this way, fuel consumption of MGT can be assessed using their partial load efficiency characteristics (Boicea, 2009, Canova, 2007, Chicco, 2007). The partial load ratio α_i is used:

$$\alpha_i(t) = \frac{P_{MGT\_i}(t)}{P_{MGT\_i\_MAX}} \quad (12)$$

Where P_{MGT_i} (kW) is the MGT electric power output, $P_{MGT\_i\_MAX}$ (kW) is the MGT rated electric power.

Based on (11) and (12) the expression for the consumed fuel thermal energy is obtained:

$$F_{MGT\_i}(t) = \frac{P_{MGT\_i}(t)}{\eta_i}.\tau = \frac{\alpha_i(t).P_{MGT\_i\_MAX}}{\eta_i}.\tau \quad (13)$$

Where τ=1800s is the time period.

By applying a cost per kWh of fuel thermal energy, the MGT operational costs in terms of fuel consumption is obtained as a function of the partial load ratio:

$$C_i = f(\frac{P_{MGT\_i}(t)}{P_{MGT\_i\_\max}}) \quad (14)$$

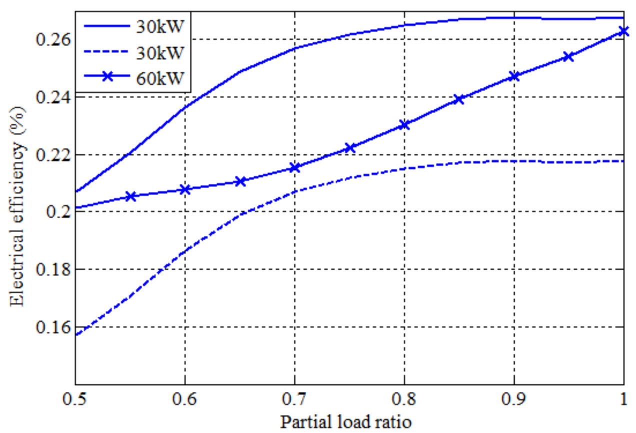

Fig. 6: Electrical efficiency as a function of partial load ratio for the three micro gas turbines

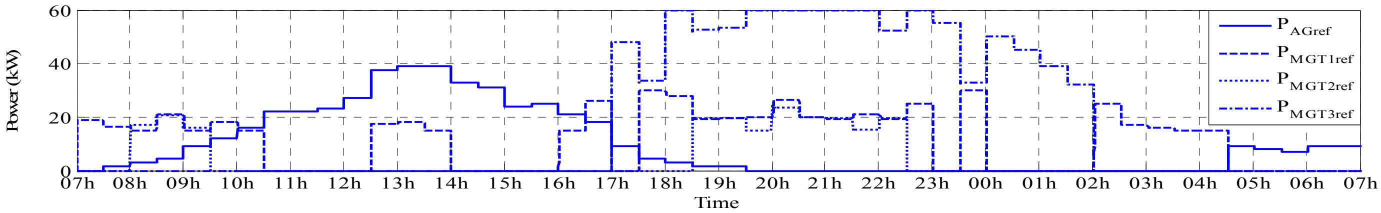

Fig. 8: Calculated power references P_{AG_ref}, $P_{MGT1ref}$, $P_{MGT2ref}$ and $P_{MGT3ref}$ (kW)

7. OPTIMIZATION RESULTS

A model of the studied system is created in MATLAB/Simulink. It comprises three micro gas turbines with rated powers of 30, 30 and 60 kW and ten PV-based active generators, each with a 4 kW peak power and loads with 115 kW peak power consumption. Due to the considerable computational power required, simulations using this model were run on a RTLab simulator at the L2EP laboratory.

Based on the 24-ahead forecasts for available PV power and power demanded to supply the loads (fig. 7), the objective function to be minimized is the consumed fuel. The optimization results are the 30 minute power references for each generator in the studied system (fig. 8).

On fig. 7 the total available PV power is greater than the power demanded to supply the loads between 10:30 and 12:00 and also between 14:00 and 15:30. In this case the excess energy is stored in the batteries of the active generators and then it is used to supply the loads in the night (P_{AGref} between 4:30 and 7:00 on fig. 8), without having to switch on any of the micro gas turbines.

Using the presented operational planning algorithm, a 8% reduction in system's operational cost over a 24 hour period is achieved, compared to a simple dispatching algorithm allocating power references to the units proportional to their rated power outputs.

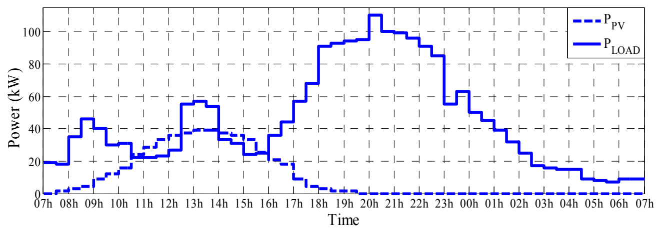

Fig. 7: 24 hour load forecast (kW) and PV power forecast in MPPT (kW)

8. CONCLUSIONS

A microgrid long and medium term operational planning are presented in this paper. Based on the forecasts of available PV energy and power, demanded to supply the loads in a microgrid, the central energy management system elaborates a 24 hour-ahead operational planning. The operational planning is optimized by the approach of unit commitment by dynamic programming. The objective function is the fuel consumption.

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