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MicroGrid Central Controller strategies and algorithms

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1. INTRODUCTION

MicroGrids comprise LV distribution systems with distributed energy sources (micro-turbines, fuel cells, PV, etc.) together with storage devices (flywheels, energy capacitors and batteries). Such systems can be operated in a non-autonomous way, if interconnected to the grid, or in an autonomous way, if disconnected from the main grid. The operation of micro-sources in the network can provide distinct benefits to the overall system performance, if managed and coordinated efficiently, as described in Deliverable "***DG1. Methods for simulating energy and ancillary services markets for Microgrids***".

In order to operate a MicroGrid in a coordinated manner it is important to provide a more or less decentralized decision making process in order to balance demand and supply coming both from the microsources and the MV distribution feeder. There are several levels of decentralization that can be possibly applied ranging from a fully decentralized approach to a hierarchical control.

Fully Decentralized Control

According to the fully decentralized approach, the main responsibility is given to the controllers of the microgenerators that compete to maximize their production in order to satisfy the demand and probably provide the maximum possible export to the grid taking into account current market prices. This approach is based on distributed multi-agent technology. The use of Multi Agent Systems (MAS) in controlling a MicroGrid solves a number of specific operational problems. First of all, microgenerators can have different owners, in which case several decisions should be taken locally, so centralized control is difficult. Furthermore, Microgrids operating in a market require that the actions of the controller of each unit participating in the market should have a certain degree of intelligence. Finally, the local DG units next to selling power to the network have also other tasks: producing heat for local installations, keeping the voltage locally at a certain level or providing a backup system for local critical loads in case of main system failure. These tasks suggest the importance of distributed control and autonomous operation.
For the fully decentralized mode of operation the following remarks should be made.

- There is no need to send a Schedule to the Distribution System Operator, since the only limits for taking or sending energy to the network are posed by the technical constraints of the installation.
- In the Microgrid MAS there is only need for an extra supervisory Agent whose primary job is to record the bids of the Micro sources and the power flow. A transaction is valid only if it is registered in the supervisory agent and this is vital in order to avoid double offers to separate loads. In Market Operation its job is to create the final bill for each load or unit.

Hierarchical Control

In order to achieve the full benefits from the operation of microgrids, as outlined in DG1, it is important that the integration of the micro sources into the LV grids, and their relation with the MV network upstream, will contribute to optimise the general operation of the system. For this purpose a hierarchical system control architecture comprising three critical control levels, as shown in Figure 1, has been adopted in this project.

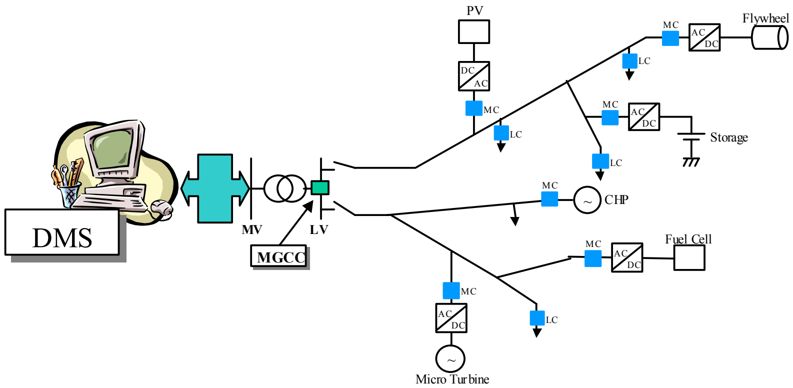


Figure 1 – Micro-Grid control architecture

- Local Micro Source Controllers (MC) and Load Controllers (LC)
- MicroGrid System Central Controller (MGCC)
- Distribution Management System (DMS).

The ***Micro Source Controller*** (MC) takes advantage of the power electronic interface of the micro source. It uses local information to control the voltage and the frequency of the microgrid in transient conditions. MCs follow the demands from the MGCC, when connected to the power grid, and have the autonomy to perform local optimization of the micro source active and reactive power production, and fast load tracking following an islanding situation. Local Micro *Load Controllers* (LC) are installed at the controllable loads to provide load control capabilities following demands from the MGCC, under a Demand Side Management (DSM) policy or for load shedding. The functions of Micro Source Controllers are described in Deliverable "***DB1. Local Micro Source Controller strategies and algorithms***".

The ***MicroGrid Central Controller*** is responsible for the maximization of the microgrid value and the optimization of its operation. It uses the market prices of electricity and probably DSM requests to determine the amount of power that the MicroGrid should draw from the distribution system, optimizing the local production capabilities. It might use simple load forecasts (electric and possibly heat) and forecasts of power production capabilities. The defined optimized operating scenario is achieved by controlling the micro-sources and controllable loads in the MicroGrid by sending control signals to the field. In this framework, non-critical, controllable loads can be shed, when necessary. Furthermore, it is necessary to monitor the actual active and reactive power of the components. These techniques can be considered equivalent to the secondary control of the interconnected grid.

Distribution Management Systems (DMS) deal with the management and control of distribution areas comprising several feeders including several MicroGrids. The traditional functions of DMS need to be enhanced with new features related to the operation of MicroGrids connected on the feeders and more generally to the operation with increased penetration of Distributed Resources. These features are outside the scope of this project.

This report is part 1 of Deliverable "***DC1. MicroGrid Central Controller strategies and algorithms***". Its purpose is to describe the functions required for the operation of the

MGCC in the interconnected mode. In particular, the following functions are dealt with in Sections 2-5:

- Forecasting Tools (short term) for electrical load and heat and for power production capabilities.
- Economic Scheduling, including load shedding and emissions calculations
- Security Assessment
- Demand Side Management (DSM) Functions

The functions of the MGCC in islanding mode of operation, like islanded operation control, synchronizing of the microgrid system with the main, black start capabilities, are dealt with in WPD and are not covered in this document.

Moreover, a flexible software tool for the optimization of the Microgrid operation under steady state security constraints is developed and described in part2 of this Deliverable. A demo presentation of the capabilities of the software "***MGCC Demo-Deliverable DCv 2.0.ppt***" is provided together with the report.

2. MGCC OVERALL ORGANIZATION

The following diagram describes a possible operation of the MGCC. It is assumed that the MGCC acts as a market operator. The local controller MC takes into account the operational cost function of the micro-source and the prices of the market provided by the MGCC, in order to make offers to MGCC and provide the limits of production. These offers are made at 15 minutes interval for the next few hours, i.e. the optimization horizon.

The MGCC takes into account:
-The prices of the market
-The bids of the micro-sources.
-The suggested limits of production
- The demand side bidding for "low" and "high' priority loads

and solves an optimization problem as described in Section 3.

The MGCC, after the optimization process is complete, sends to the Local Controllers:
-The prices of the market for the optimization horizon at 15-minutes steps
-The set-points for active and reactive power.
- The load to be shed or served according to Demand side bidding option followed.

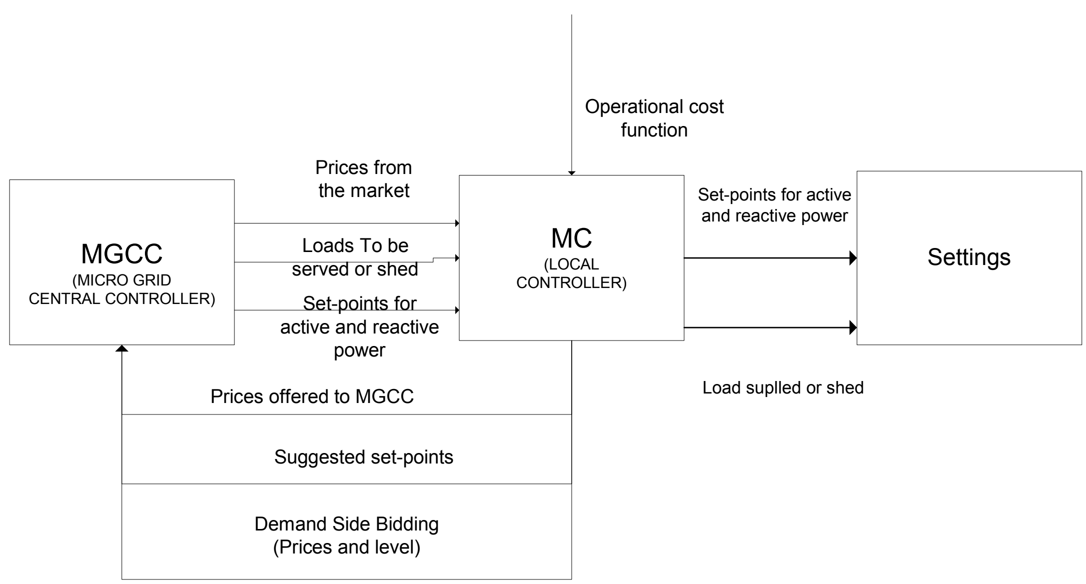


Figure 2.1.Closed loop for energy markets- Information exchange diagram

3. ECONOMIC SCHEDULING

3.1 Market Policies

"Good Citizen": The Microgrid serves only its own consumers requesting zero reactive power from the grid

According to the prices of the market and the production cost, the MGCC tries to meet the active power demand. When the market prices are high, this usually means that there is peak demand at the whole grid. Due to the high prices, it is beneficial for the microsources to produce energy in order to minimize the Microgrid cost of operation. On the other hand, the Microgrid tries to maintain zero reactive power demand from the grid, if possible.

The term "good citizen" is used because:

1. The distribution grid is not burdened by the reactive power demand of the Microgrid, so that grid voltage control is made easier
2. At the time of the peak demand and high prices, the Microgrid relieves possible network congestion by supplying some of its energy needs.

In this case, MGCC is provided with:

1. The market prices active and reactive power (A Ect/kWh, B Ect/kVarh)
2. The active and reactive power demand (Pdemand, Qdemand), probably as a result of a short term load forecasting tool.
3. The bids of the microgenerators.

The MGCC tries to minimise the energy costs for the whole Microgrid solving the following optimization problem for each of 15 minutes interval.

$$\text{Minimise } \cos t = \sum_{i=1}^{N}(a_i x_i^2 + b_i x_i + c_i) + AX + \sum_{k=1}^{M}(a_k y_k^2 + b_k x_k + c_k) + BY \quad (3.1.1)$$

Subject to :

1. Active and reactive power balance

$$\left.\begin{aligned} X + \sum_{i=1}^{N} x_i &= Pdemand \\ Y + \sum_{k=1}^{M} y_k &= Qdemand \end{aligned}\right. \quad (3.1.2)$$

2. P-Q curve for each one of the generator units and the grid.
M units with Active power, N units of reactive power.

$$\sqrt{(x_m^2 + y_m^2)} \leq s_m^{MAX} \text{, for each } m \in (M+N) \quad (3.1.3)$$

3. Technical limits of each unit

$$P_i^{\min} \leq x_i \leq P_i^{MAX} \quad (3.1.4)$$

$$Q_k^{\min} \leq y_k \leq Q_k^{MAX} \quad (3.1.5)$$

x_i : active power production of microgenerator i.

y_k : reactive power production of microgenerator k (or capacitor, etc)

X: active power bought from the open market

Y: reactive power bought from the open market (zero,unless needed)

$a_i x_i^2 + b_i x_i + c_i$: Formulation for the active power bid of generator i. This can be an approximation of the bid or it can reflect the operational cost function that is usually quadratic. The Local controller may for example suggest as bid, the operation cost function increased by a profit margin.

$a_k y_k^2 + b_k \cdot y_k + c_k$: reactive power bid offered to the aggregator

Ideal Citizen: The Microgrid participates on the market by buying and selling active and reactive power from/to the grid

It is assumed that the Microgrid serves its own needs, but it also participates in the market offering bids via an aggregator. The MGCC tries to maximise the value of the Microgrid, maximising the gains from the power exchange with the grid

The MGCC is provided with:

1. The market price for buying and selling active (A Ect/kWh) and reactive power (B Ect/kVarh) to the grid. The same prices apply to the consumers within the Microgrid.
2. The active and reactive power demand, probably from a short-term forecasting tool
3. The bids of each microsource regarding active and reactive power under the following form: $(a_i x_i^2 + b_i x_i + c_i)$ in Euro where x_i is the production in kW.
4. The maximum capacity allowed to be exchanged with the grid. This can be for example some contractual agreement of the Aggregator or the physical limit of the interconnection line to the grid.

The MGCC provides:

1. Set points of the microsources.
2. Active power X and reactive power Y bought from the grid
3. Active and reactive power sold to the grid.

The objective function is:

Maximise(MicrogridsValue)

equivalent to (3.1.6):

$$\boxed{\text{Maximise \{Income-Expenses\}}}$$

The objective function is formulated as:

$$Max\left\{ A\sum_{i=1}^{N} x_i - \sum_{i=1}^{N}\left(a_i x_i^2 + b_i x_i + c_i\right) + B\sum_{k=1}^{M} y_k - \sum_{k=1}^{M}\left(a_k y_k^2 + b_k y_k + c_k\right)\right\} \quad (3.1.7)$$

x_i : active power of microsource i.

y_k : reactive power of microsource k (generator, capacitor etc)

N the number of active power units, M the number of reactive power units

If active power X is bought from the grid at A Ect/kWh, costing AX, the same amount will be also received from the consumers of the Microgrid, since we have assumed the same prices. This is why X and Y are omitted in (3.1.7).

The following **constraints** are applied:
1. The technical limits of the micro-sources

$$P_i^{\min} \leq x_i \leq P_i^{MAX} \quad (3.1.8)$$

$$Q_k^{\min} \leq y_k \leq Q_k^{MAX} \quad (3.1.9)$$

Where

x_i : the active power production of the μ-source i.

y_k : the reactive power production of μ-source k (generator, capacitor etc)

2. P-Q curve for each one of the micro-sources. M units with active power, N units with reactive power.

$$\sqrt{(x_m^2 + y_m^2)} \leq s_m^{MAX} \quad (3.1.10), \text{ for each } m \in (M+N)$$

3. The capacity of the interconnection:

$$ApparentPower \leq ApparentPowerCapacity \quad (3.1.11)$$

The apparent power capacity can be the thermal rating in kVA of the interconnection, the transformer or the contracted capacity with the Aggregator.

4. Constraints reflecting limits of total generation

$$\sum_{i=1}^{N} x_i \leq Pdemand + ConnectionLineCapacity \quad (3.1.12)$$

This constraint means that the active power produced by the micro-sources should not exceed the active demand and the capacity of the interconnection or the active power contracted by the Aggregator.

$$\sum_{i=1}^{N} x_i \geq \max\{0, Pdemand - ConnectionLineCapacity\} \quad (3.1.13)$$

The above constraint reflects the case when the connection line capacity or the power bought from the grid is constrained. Therefore the micro-sources should produce the necessary active power to meet the demand without violating the constraints expressed by the second term of the maximum function.

3.2 Steady State Security

In large power systems, steady state security is the state of the system characterized by no limit violation in its actual (pre-contingency) or potential (post-contingency) operation. For Microgrids, the most relevant contingency is the loss of the interconnection due to a fault in the main grid. In this Section, steady state security is examined in the sense of adequacy, i.e. it is examined whether the micro-sources can meet the total demand of the Microgrid, in case of interconnection loss. If the system has adequate generation capacity, it is considered as steady state secure, otherwise it is considered insecure.

If the Microgrid is steady state secure, then μ-sources that can meet the demand should be at least committed and dispatched at their technical minima so that if the grid disconnection takes place these units can meet the islanded demand. This operation is clearly uneconomical, it becomes however interesting, if combined with load management (shedding) strategies.

An interesting issue with respect to steady state security of a Microgrid, is the requirement to maintain voltages at the consumer points within acceptable limits, typically ±5% of the nominal voltage. In order to satisfy this requirement, a Load Flow routine is developed that checks the output of the optmization algorithm and rejects the solution, if voltage limits are not met. In this case micro-sources may need to be committed or increase their production – if the voltage is lower than the lower acceptable limit- or lower their production, if the voltage is above the maximum acceptable voltage limit. The Load Flow algorithm is described in section 3.4.1.

Since there is one interconnection with the main grid, i.e. the MV/LV transformer, the voltage drop in the transformer changes as the power exchange with the main grid changes. Therefore, if the production of the micro-sources is increased, the voltage at the consumers increases. On the contrary, if the production of the micro-sources decreases, voltages also decrease. Thus, if there is a need for voltage increase there extra production from the micro-sources, otherwise the micro-sources must decrease their production.

When voltages are lower than the acceptable limits, the production of micro-sources should increase, as defined by the following approximate equation:

$$RP + XQ = (lowVoltage\lim it - \min Voltage) * \min Voltage \quad (3.1.14)$$

P, Q are the additional active and reactive power production needed from the micro-sources. *LowVoltagelimit* is the acceptable lower limit for the voltage and *minVoltage* the value of the minimum voltage at the consumer buses of interest. R and X are the values of the interconnection transformer.

Similarly, micro-sources should lower their production according to:

$$RP + XQ = (\max voltage - HighVoltage) \cdot \max voltage \quad (3.1.15)$$

P, Q are the active and reactive power production from the micro-sources, *HighVoltagelimit* the acceptable higher limit for the voltage, *maxVoltage* the value of the maximum unacceptable voltage and *R* and *X* are the values of the interconnection transformer.

To simplify the problem, it is assumed that only the active power of the microsources is modified. The modification is defined by the above two equations (3.1.14) and (3.1.15). This modification creates a lower/upper bound of production for the microsources depending on the low/high voltages. If the committed units are sufficient to meet demand under these constraints, the power is re-dispatched to the committed microsources with economic criteria. If they are not sufficient, new micro-sources have to be committed and the Unit commitment algorithm is called.

3.3. Demand Side bidding aspects

It is assumed that loads at the customers are equipped with load controllers. Each consumer may have low and high priority loads and sends separate bids to the MGCC for each of them. In this way the total consumption of the consumer is known in advance. Some of the loads will be served and others not, according to the bids of both the consumers and the micro-source producers. For the loads that the MGCC decides not to serve, a signal is sent to the load controllers in order to interrupt the power supply.

Two options are considered for the consumers' bids:

A) Consumers bid for supply of high and low priority loads
B) Consumers offer to shed low priority loads at fixed prices in the next operating periods.

In both options the MGCC:

1. Accepts bids from the consumers every hour corresponding to quarter of an hour intervals.
2. Informs each consumer about acceptance of his bids
3. Informs consumers about the prices of the open market. These prices help preparing the bids. For Microgrid operation as a good citizen, the market prices will be the upper bound of prices if steady state security constraints are not considered.

Option A

It is assumed that each consumer places bids for his own load in two levels and the prices of the bids reflect his interest for each load block. The "low" priority loads are the ones the consumer prefers not to operate when the market prices are high, and can be served later, when prices are lower (shift) or not served at all (curtailment). The MGCC knows the total low and high priority loads and decides which of them to serve and which not, based on the optimization function outcome. A possible formulation of the customer bid might be:

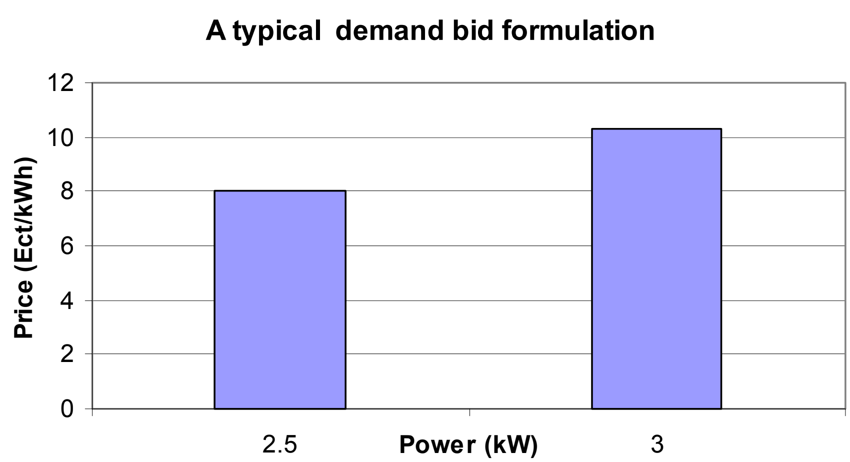


Figure 3.2.1 Typical Bid formulation

In this example, the consumer has a total demand of 5.5kW=(2.5+3kW). He offers a lower price for a low priority block, such as the water heater.

The MGCC aggregates the demand bids, the production bids and the open market prices and decides which bids will be accepted. The total demand of the Microgrid is the summation of the accepted demand bids. A typical formulation of this procedure is shown in Figure 3.2.2. In this example the demand of the Microgrid that will be satisfied is 75kW.

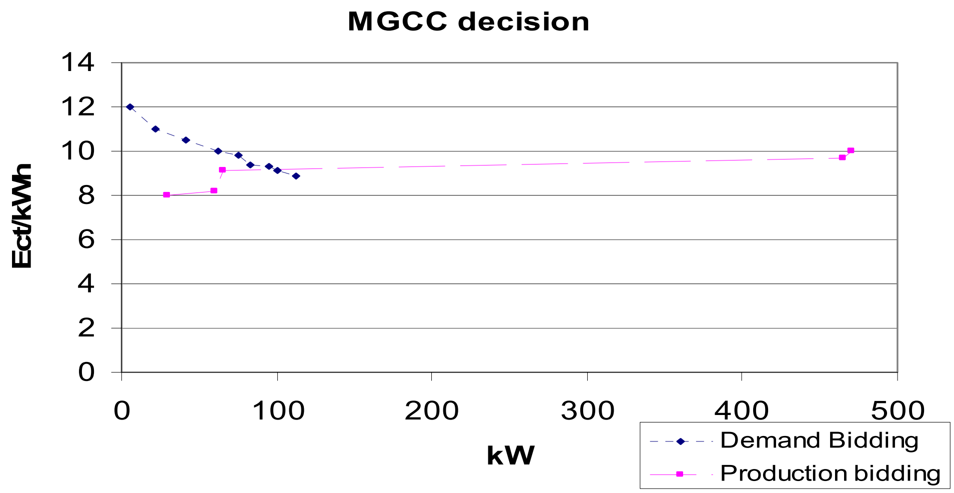


Figure 3.2.2 The Decision for the MGCC according to the bidding

Information about the open market prices influences consumer bids, i.e. might shift load for a while in order to achieve lower costs for his electricity consumption. Short-term load forecasting is less relevant.

Option B

In this case each consumer states the amount of load that can be shed in the next operating period. It is assumed that load can be shed in maximum two steps. The consumer will be compensated for his service, if his bid is accepted. In this option the MGCC has the right to shed "cheaper" loads, if they are on. Loads to be shed are considered as "negative" generation, if they are cheaper than actual generation, lowering the total demand. A typical formulation of the respective bid is described in Figure 3.2.3. In this example, the consumer states that 2.5 kW is of lower priority and can be shed at 5 Ect/kW, while if the consumer is paid 10.3 Ect/kW he is willing to have all of his demand shed.

The MGCC takes into account the bids for shedding, the bids of production and either the aggregation of the total demand as the actual total demand to be met (5.5kW for this customer) or a forecasted demand (*Actual_demand*) and accepts the demand shedding bids. (*demand_shed_bidding_accepted*). The total demand that will finally be met in the Microgrid is *Actual_demand-demand_shed_bidding_*accepted.

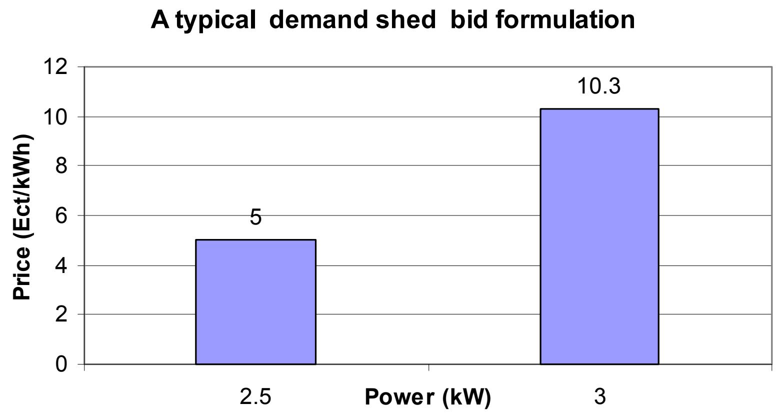


Figure 3.2.3 Typical pattern for shedding bids

3.4 Solution Methods

In order to optimize the operation of a power system two functions are required:

- Unit Commitment (UC) function, that determines which micro-sources will be committed at each time interval
- Economic Dispatch (ED) function, that determines the operating point (power) of each production unit (and load, if applicable).

A variety of methods have been applied to solve the above problems.

In the Microgrid studies the following techniques have been used:

- Priority list for the UC and ED functions for "good citizen" policy.
- Priority list for UC, Sequential Quadratic Programming (SQP) for ED for "ideal citizen" policy.
- Ant-colony optimization for UC and ED for both policies

3.4.1 Priority list

Priority list methods have been widely used by Electric Utilities due to their simplicity.

UC function

1. Reads minimum and maximum capacity of the production units
2. Reads open market prices. The grid (open market) is considered as a "virtual", large generator with maximum capacity determined by the congestion limit of the interconnection. Therefore the units taking part in the market are number of micro-sources+1.
3. Creates priority list sorted according to the differential cost of each unit – ratio of cost in maximum capacity to maximum capacity of each one of the micro-sources.
4. The cheapest units are committed until the demand plus an amount of spinning reserve are covered. One of these units may be the grid. In our application, a 10 % spinning reserve of the requested load is assumed. This is of-course user-defined.

ED function

1. Reads minimum and maximum capacity of the production units
2. Reads open market prices. As above, the open market is considered as a "virtual" generator with maximum capacity the congestion limit of the interconnection

3. Creates priority list sorted according to the differential cost of each micro-source $(\cos t\_at\_\max imum\_capacity - \cos t\_at\_\min imum\_capacity)/(\max imum\_capacity - \min imum\_capacity)$ committed and the market.
4. All units committed are dispatched at least at their technical minima.
5. Active demand is dispatched to the committed units, according to the priority list, so that the active power demand is met.

Software Development

Code for Unit Commitment and Economic Dispatch functions for the "Good Citizen" Policy has been developed in Visual Basic 6 and is included in Part 2 of this report. A short overview is provided in the following displays:

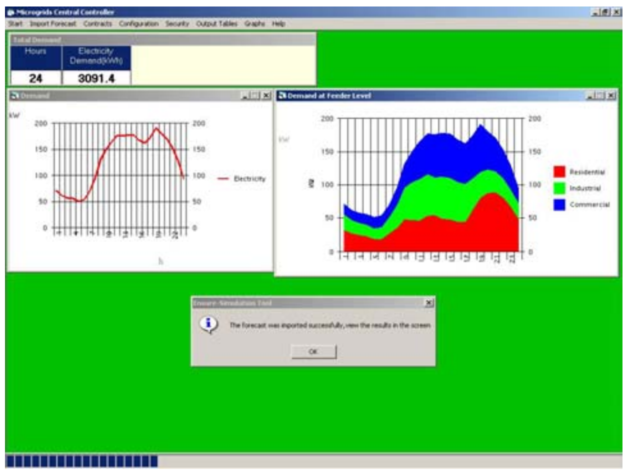


Figure 3.4.1 . The demand screen

In 3.4.1 the total Microgrid demand and the demand per feeder are displayed.

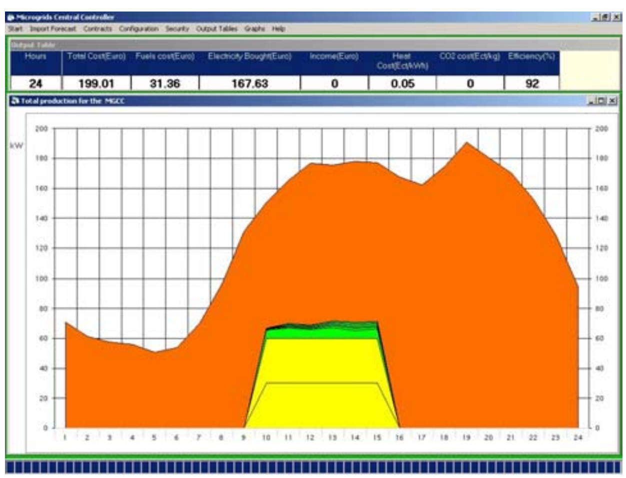


Figure 3.4.2. The Output Screen

In 3.4.2 the results of the optimisation routines are shown. The user can view the economic scheduling plan for the optimisation period and display information about costs and energy balance.

Dealing with Steady State Security

If a fault takes place in the grid, the survival of the Microgrid depends on the amount of the available spinning reserve, i.e. if it is sufficient to compensate for the loss of the power fed by the interconnection. Maximum steady state security means that, when the capacity of the micro-sources is sufficient for meeting the demand of the Microgrid, the MGCC should try to commit the necessary units for meeting the demand. In this way the necessary spinning reserve to compensate grid disconnection will be maintained, although this might be clearly not the most economical solution. If the capacity of the micro-sources is not enough to meet the demand, in case of grid disconnection, the Microgrid will collapse, unless it activates load shedding.

To deal with Steady State Security, as described above, the Unit Commitment algorithm is modified, so that during the hours the micro-sources are sufficient to meet demand, they are committed according to their positions in the priority list excluding the virtual "open market" unit, until demand is met. In the Economic Dispatch procedure, active power is dispatched to the micro-sources and if it is economically beneficial, active power is also bought form the grid. In such case, the micro-sources are adequate to meet demand, in case of loss of interconnection in the most economic way. During the hours the micro-sources are not sufficient to meet demand, they are committed according to their positions in the priority list, as long as they are cheaper than the open market prices. The rest of the demand is met by power bought from the grid. The Microgrid is then insecure in case of loss of the interconnection. This can be displayed on call, as shown in Figure 3.4.3.

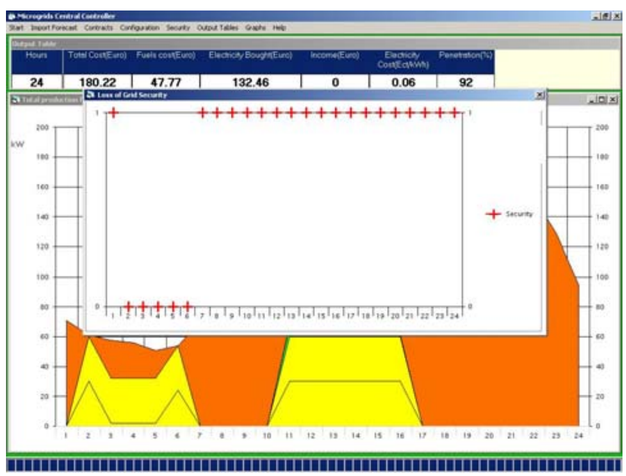


Figure 3.4.3. The final screen with steady state security indexes.

In this example during the hours 2-6 the system is steady-state secure, in case of a fault in the main grid, since the committed micro-sources can meet demand. Actually, for these hours the micro-sources seem to offer competitive prices to meet the whole demand, instead of buying from the grid. This can be so, because of the high open market prices and the relatively low b_i factor of the micro-sources committed. For the rest of the hours the Microgrid is steady-state insecure, in case of loss of interconnection.

Dealing with Demand side bidding

In order to implement option A of the demand side bidding in the Good citizen Policy, the following modifications have been made to the UC and ED algorithms.

Each demand bid is considered as a 'negative' generator. Therefore the bids of the consumers are placed in the same priority list with the bids of the generators. If the value of the consumer bid is lower than the value of a producer bid, then the total demand is reduced by the load offered to be shed by the consumer bid. The Unit Commitment function takes into account both demand and production bids in order to decide which loads to be shed and which microsources to be committed.

The total Microgrid demand is lowered by the summation of the shed bids accepted. Since the demand bids are of discrete nature, there is no optimization process to determine "exact" operating points for the controllable loads. Therefore the Economic Dispatch function does not require any modifications, except that the total load is reduced.

Figure 3.4.3 displays how much load is possibly shed in case of grid disconnection in two cases.

a. Bids for disconnection of low priority loads are accepted
b. There are no priority loads.

The lower curve shows the demand to be shed even if the low priority loads have been shed. The upper line shows the total demand shed in case of grid disconnection.

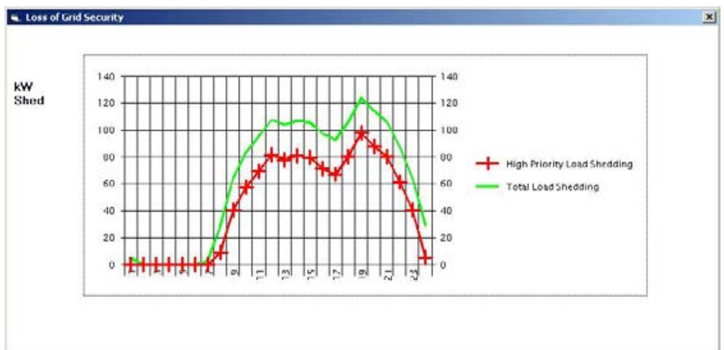


Figure 3.4.4. Load to be shed in case of grid disconnection

3.4.2 Priority List - Sequential Quadratic Programming

UC function

In order to implement the "ideal citizen" policy, this function is slightly modified compared to the UC function of Section 3.4.1, in order to take into account the possibility of selling power to the grid.

The steps followed are:

1. Maximum load for Unit Commitment is computed: It is the demand plus the capacity of the interconnection line plus an amount of spinning reserve.
2. The differential cost of each of the micro-sources is computed and the values are placed in a priority list
3. The differential cost of the market price is computed and is placed in the above table.
4. The elements of this list are sorted in ascending order.
5. Micro-sources are committed until the grid is committed. The unit Commitment process stops, unless the power supplied by the grid is constrained by the interconnection line. In such a case, more expensive μ-sources than the open market prices are committed, so that the demand is met.

The Unit commitment algorithm is described in the following flow chart:

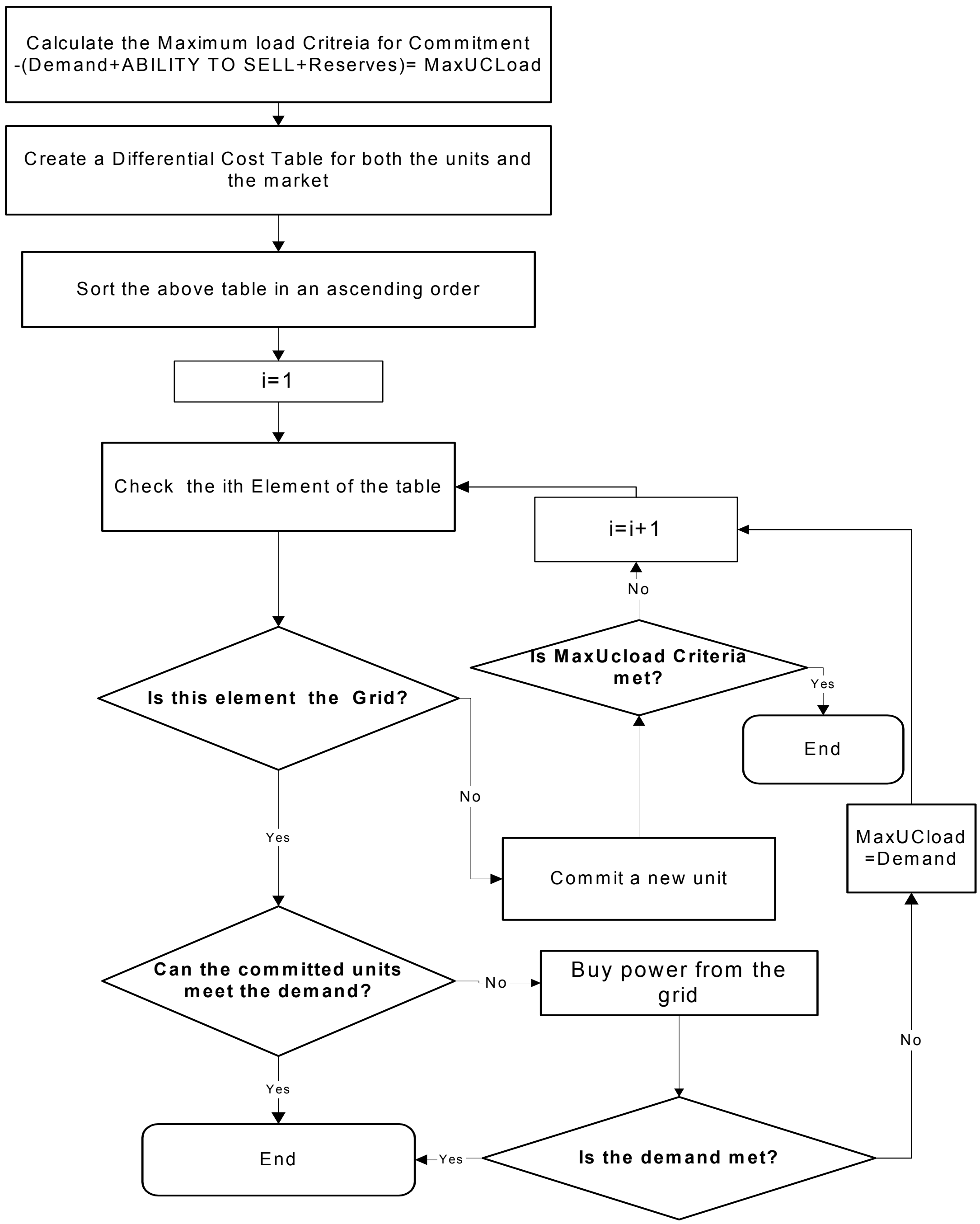


Figure 3.4.5 Unit Commitment Process

ED function

The Sequential Quadratic Programming is used. This is a generalisation of the Newton's optimisation method, which uses a quadratic approach of the objective function and linear approximations for the constraints of the problem. This method guarantees that the solution found is the global optimum in the feasible space, if the objective function is convex, as in our case-equation 3.1.7. The following constraints are applied:

- Minimum and maximum production of micro-sources (3.1.8),
- Capacity of interconnection (3.1.9),
- Constraints for power production (3.1.10),(3.1.12).

In the following, the Sequential Quadratic method is briefly described:

This optimisation method assumes a quadratic objective function, such as:

$$q_k(d) = \nabla f(x_k)^T \cdot d + \frac{1}{2} \cdot \nabla^2_{xx} \cdot L(x_k, \lambda_k) \cdot d \quad (3.4.1)$$

This problem is solved using the following: Find a vector X that minimises the following function

$$Q = \nabla f^T \Delta X + \frac{1}{2} \Delta X^T \left[\nabla^2 L\right] \Delta X \quad (3.4.2)$$

subject to the following constraints :

$$g_j + \nabla g\, h_j^T \Delta X \le 0 \quad j = 1,2,...,m \; (3.4.3)$$

$$h_k + \nabla h_k^T \Delta X = 0 \quad k = 1,2,...,p \; (3.4.4)$$

and the Lagrange Function given by the following equation

$$\tilde{L} = f(X) + \sum_{j=1}^{m} \lambda_j h_k(X) + \sum_{\kappa=1}^{p} \lambda_{m+k} h_k(X) \quad (3.4.5)$$

The ΔX vector is then assumed to be a vector S for which the method will be applied and the problem is transformed as:

$$Q(S) = \nabla f(X)^T S + \frac{1}{2} S^T \left[\nabla^2 L\right] S \quad (3.4.6)$$

subject to the constraints

$$\beta_j g_j(X) + \nabla g_j(X)^T S \le 0, \qquad j = 1,2,...,m \quad (3.4.7)$$

$$\bar{\beta} h_k(X) + \nabla h_k(X)^T S = 0, \qquad k = 1,2,...,p \quad (3.4.8)$$

where [H] is a positively defined matrix used to converge to the Hessian matrix of the Lagrange Function. This table is updated at each step using the BFGS formula in such a way that the table remains positive defined.

β_j and $\bar{\beta}$ are typical constants to avoid cutting off the solution space entirely. Typical values of these constants are:

$$\bar{\beta} \approx 0.9 \text{ and } \beta_j = \begin{Bmatrix} 1 \text{ if } g_j(X) \le 0 \\ \bar{\beta} \text{ if } g_j(X) \ge 0 \end{Bmatrix} \quad (3.4.9)$$

The Lagrange multipliers are calculated using the formula $\lambda = (G^T G)^{-1} G^T F$, where G the first derivative of the active constraints and F the first derivative of the objective function. Then the vector X is updated using the following equation:

$$X_{j+1} = X_j + \alpha^* \cdot S \quad (3.4.10)$$

where α* is the optimum step towards the direction S and is found minimising the following function :

$$\phi = f(X) + \sum_{j=1}^{m} \lambda_j (\max[0, g_j(X)]) + \sum_{\kappa=1}^{p} \lambda_{m+k} \left|h_k(X)\right| \quad (3.4.11)$$

with

$$\lambda_j = \begin{cases} |\lambda_j|, j = 1,2,\dots,m+p, in\ first\ iteration \\ max\left\{|\lambda_j|, \frac{1}{2}(\tilde{\lambda}_j, |\lambda_j|)\right\} in\ subsequent\ iterations \end{cases} \quad (3.4.12)$$

Software Development

Code for Unit Commitment and Economic Dispatch functions for the "Ideal Citizen" Policy has been developed in MatLab® 5.3. A short overview is provided in the following displays:

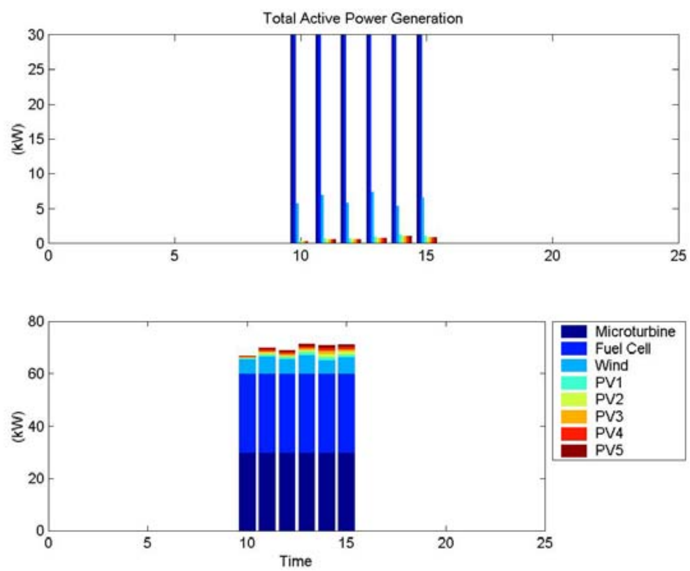


Fig.3.4.6. Economic Scheduling of the Micro-sources

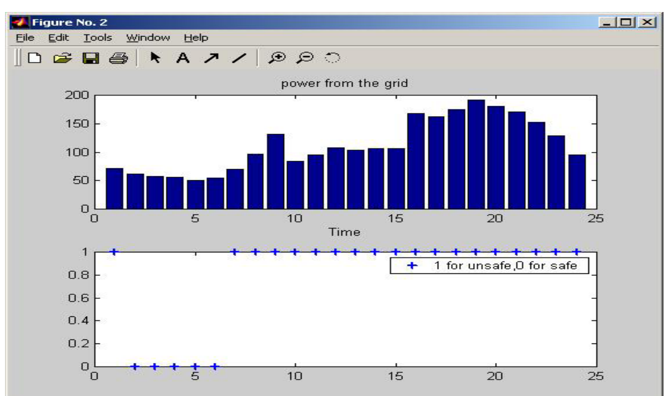
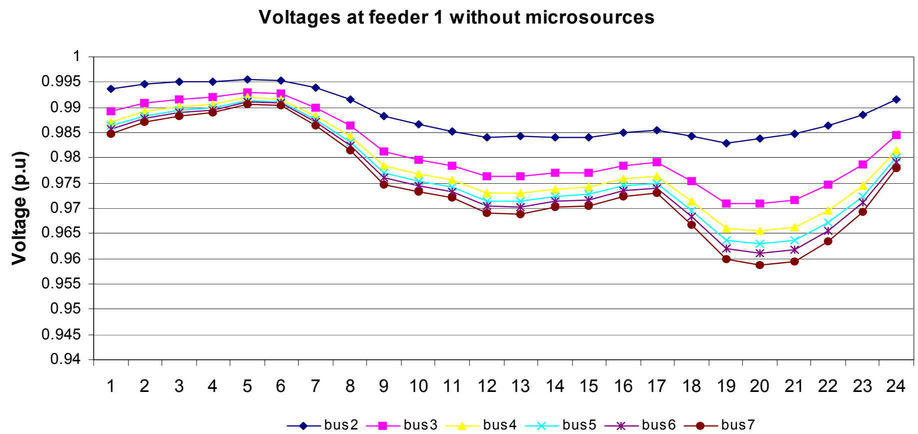
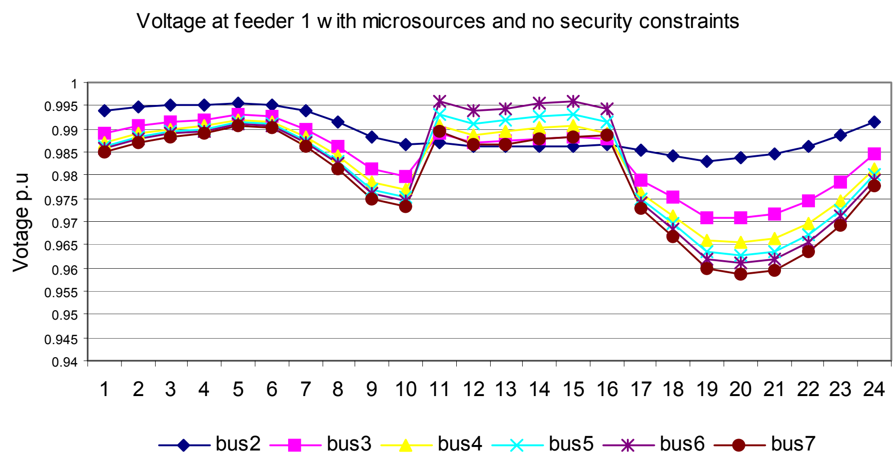


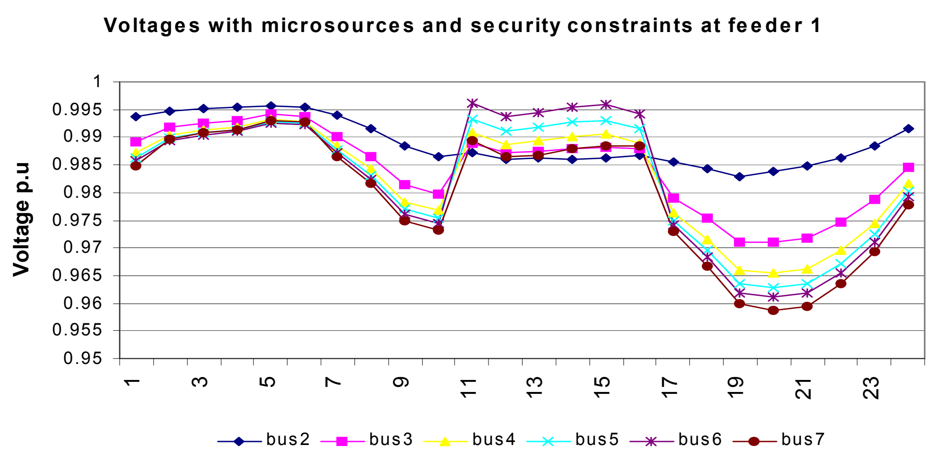
Fig 3.4.7. Power exchanged with the grid (positive – energy bought from the grid, negative – energy sold)

Load Flow Function

A load flow routine was developed in MATLAB based on the Newton Raphson algorithm and added to the code developed for implementing the "Ideal Citizen" policy. In this way the voltage profiles at each one of the buses can be provided at each step of the optimization horizon. Indicative voltages in the cases of a) zero production from the microsources and b) production profile from microsources as given by the optimization process are shown in the following diagrams:







Dealing with Steady State Security

The Unit commitment function is modified, similarly to the "Good Citizen" policy, i.e. when the micro-sources are capable to meet the total demand of the Microgrid, they are committed, in order to face grid disconnection. Whether the Microgrid is capable to meet its own demand is shown in the lower screen of Fig 3.4.7. The load flow results provide if the voltages are within the specified limits. If not, the Economic Dispatch, and if necessary the Unit Commitment are repeated, taking into account the lower or the upper limit of production from the microsources so that the voltages are kept within the specified limits.

Dealing with Demand Side Bidding

For Load option A, the necessary modifications are similar to the "Good Citizen" policy. As before, the demand bids are regarded as negative production and the total demand is modified accordingly. The demand side bidding mainly modifies the power exchange with the grid.

In this case however, the Aggregator has to reward on top of the micro-sources production, the loads to be shed. The active power produced by the micro-sources is sold either to the Microgrids consumers or to the grid at the same price. The income received by selling the active power of the microsources is the same either the load is shed or not. Therefore, if there is load shed then the revenues for the Microgrid will be reduced if the load bids are accepted.

3.4.3 Ant Colony Optimisation

Collective intelligence studies how the actions and inter-relations of a set of simple agents (e.g. ants) carry out global objectives of the system where these agents are immersed (e.g. power system). Each agent collaborates in the realization of the tasks to complete those objectives, without central coordination or control, through mechanisms of inter-relation and communication between them. In these systems, their agents are not individually intelligent, but their actions as a whole have an intelligent behavior in order to complete certain objectives of the system (for example the search of food sources by ants). Real ants are capable of finding the shortest path from a food source to their nest without using visual cues by exploiting pheromone information While walking, ants deposit pheromone trails on the ground and follow pheromone previously deposited by other ants. The above behavior of real ants has inspired the Ant Colony System (ACS), an algorithm in which a set of artificial ants cooperate to the solution of a problem by exchanging information via pheromone deposited on ACS-graph. The main characteristics of the ACS are:

- it follows a positive feedback (it allows finding good solutions quickly),
- it is based on distributed computation (it avoids premature convergence),
- it uses a constructive greedy heuristic (it helps find acceptable solutions) and
- it is a population-based approach.

The ACS algorithm in power system scheduling applications works as follows:

Each artificial ant generates a complete tour by choosing predefined values (states) of chosen control variables (stages) of a power system (e.g. Microgrid) according to probabilistic state transition rule: Ants prefer to "move" to states of control variables which are "connected" by trails with a high amount of pheromone. The role of pheromone plays an objective function of the power system to be optimized. Once all ants have completed their tours a pheromone-updating rule is applied: A fraction of the pheromone evaporates on all trails and then each ant deposits an amount of pheromone on trails, which belong to its tour (the value of its achieved objective function). The process is then iterated.

The ACS algorithm is applied in the operation of Microgrid Central Controller (MGCC) , since each policy corresponds to an objective function to be optimized. The proposed ACS algorithm is analyzed, and results obtained by the application on the Microgrid operation are represented.

Steps for ACS algorithm
1. Repeat until create the ACS-graph
1.1 Enumerate those active power μ-sources + grid *(stages)* that satisfy expected load and spinning reserve (usually 10% of the load) during the time-intervals
1.2 Enumerate all settings *(states)* of above active power μ-sources + grid at each time-interval.
2. Insert the pheromone matrix $\gamma(G,S)$ according to nodes of ACS-graph, where S is the number of stages and G the number of states.
3. Initialize the pheromone matrix $\gamma(G,S) = \gamma_0(G,S) = \tau_{max}$ (in (8), in this case f_{gbest} is an initial estimation of the best solution).
4. Repeat until the system convergence or iteration is less than a given maximum number
4.1 Place randomly M ants on the states of the 1^{st} stage (t = 1)
4.2 For k = 1 to M
4.2.1 For t = 2 to T
4.2.1.1 When the ant-k has selected the r-state of the (t-1)-stage, it currently chooses the s-state of the (t)-stage in which will move according to transition rule (1)
4.2.1.2 Move the ant-k to s-state of stage-t
4.2.1.3 Record s to J^k, and set r =s
4.2.2 Calculate the multi-criteria objective function (4) for each ant
4.2.3 Update the pheromone of (r,s)-trails for each ant, using the local pheromone update formulae (2), (3)
4.2.4 Update the pheromone of (r,s)-trails belonging to best ant tour (f_{best}), using the pheromone update formula (6)
4.2.5 In order to avoid the ants stagnations, enforce the limits (7)-(9

Mathematical Formulation

If the ant k is at point r, has the next point been visited? The ant k maintains a tabu list N_r^k in memory that defines the set of states still to be visited when it is at point r. The ant k chooses to go from state r to state s during a tour in accordance with the transition rule:

$$s = \arg\max_{\ell} \left(\frac{\gamma(r,s)}{\sum_{l} \gamma(r,\ell)} \right) \qquad s,\ \ell \in N_r^k \qquad (3.4.13)$$

where: matrix $\gamma(r,s)$ represents the amount of the pheromone trail between states r and s.

Then, the pheromone trail on coupling (r,s) is updated according to:

$$\gamma(r,s) = \alpha \cdot \gamma(r,s) + \Delta\gamma^k(\mathrm{r,s}) \qquad (3.4.14)$$

where: α with 0<α<1, is the persistence of the pheromone trail, so that (1-α) to represent the evaporation (a = 0.999) and $\Delta\gamma^k(r,s)$ is the amount of pheromone that ant k puts on the trail (r,s):

$$\Delta\gamma^k(r,s) = \frac{1}{Q \cdot f} \qquad (3.4.15)$$

where: Q is a large positive constant (Q = 1000000) and f is the objective function.

Objective function of market policies of the Microgrid formulated for ACS algorithm

Good citizen policy

The formulation of the objective function for the ACS algorithm is given below.

$$f = \sum_{t=1}^{T}\left(A_t \cdot P_t + \sum_{i=1}^{N_t}\left(a^i \cdot P_t^{i2} + b^i \cdot P_t^i + c^i + S_t^i\right)\right) \qquad (3.4.16)$$

A_t (Ect/KWh)is market prices for buying/selling active power to the grid at time-interval t,
P_t is active power buying (P_t> 0.0) from the grid at time-interval-t,
P_t^i is active power production of μ-source-i at time-interval-t,
a^i, b^i, c^i are coefficients of power production cost function of μ-source i,
S_t^i is incremental start-up cost of μ-source-i at time-interval-t,
N_t is number of active power μ-sources at time interval-t,
T is the total number of time-intervals.

If any constraint is violated the objective function (3.4.16) is highly penalized, e.g. violation of the power balance means that the bellow penalty factor is added to the objective function:

$$Pf_b = Pb \cdot \sum_{t=1}^{T}\left(P_t + \sum_{i=1}^{N_t} P_t^i - P_D - P_{spr}\right)^2 \qquad (3.4.17)$$

P_D is total power demand of the grid at time-interval-t,
Pb is a high constant value (Pb = 50000),
P_{spr} is the spinning reserve P_{srb} = 10% P_D.
Other constraints can be enforced in the same way.

Ideal citizen's policy

The MGCC tries to maximize the value of the Microgrid maximizing the gains from the power exchange with the grid. The selling prices either to the grid or to the customers of the Microgrid is the price of the open Market. The cost or even the revenues from this policy will be transferred to the end users of the Microgrid.

When all ants complete their tours, the pheromone trails (r,s) of the best ant tour (ant with minimum objective function f_{best}) is updated (global update) as:

$$\gamma(r,s) = \alpha \cdot \gamma(r,s) + \frac{R}{f_{best}} \qquad r,\ s\ \in N_{best}^k \qquad (3.4.18)$$

where: R is a large number (R = 4000000) and a = 0.999.

To avoid search stagnation (the situation where all the ants follow the same path, that is, they construct the same solution), the allowed range of the pheromone trail strengths is limited to:

$$\gamma\ (r,s)=\begin{cases}\tau_{\min} & \text{if } \gamma\ (r,s)\le\tau_{\min} \\ \tau_{\max} & \text{if } \gamma\ (r,s)\ge\tau_{\max}\end{cases} \qquad (3.4.19)$$

For our study the limits are chosen as:

$$\tau_{\max}=\frac{1}{\alpha\ \cdot f_{gbest}} \qquad (3.4.20)$$

where: f_{gbest} is the global best solution (best over the whole past iterations), and

$$\tau_{\min}=\frac{\tau_{\max}}{M^2} \qquad (3.4.21)$$

where M is the number of ants (M = 300).

3.5 Indicative Results

In this Section indicative results obtained from the application of the above methods to the LV network adopted as the Microgrids "Study Case LV Network", defined in WPA – TA5. Study Case Definition also shown in Appendix.. This is included in the Appendix. Detailed results will be provided in Deliverable "***DC2. Description and Evaluation of Microgrid Controller Strategies***".

3.5.1 Study Case 1 –Three feeders

The load pattern is given from the following table

Hour	Active Load (kW)	Hour	Active Load (kW)
1	70.663	13	175.511
2	61.331	14	177.848
3	57.376	15	177.028
4	55.745	16	167.358
5	50.705	17	162.077
6	53.936	18	174.144
7	69.93	19	191.028
8	96.183	20	180.202
9	131.316	21	170.208
10	150.543	22	152.49
11	165.353	23	129.023
12	176.727	24	94.677

The following are examined :

1. No micro-source production, all demand satisfied by the grid.
   The calculated cost 177.17 Euro
2. Good Citizen Policy : Calculated cost 165.4 Euro
3. Ideal Citizen Policy : Calculated cost 165.4 Euro

The reason that the cost in both Market policies is the same is that the micro-sources have not sufficient capacity to meet the Microgrid demand and also sell to the grid. The cost reduction by the operation of the micro-sources is **11.77 Euro** or **6.6%** of the cost.

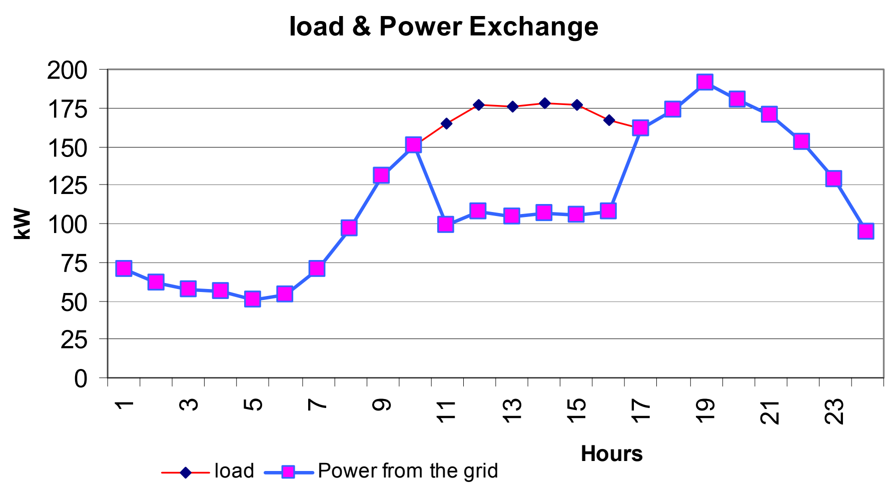


Figure 3.5.1. Load and Power Exchange for all three feeders

3.5.2 Study Case 2 – Only Feeder with DGs

In this case only the feeder with the micro-sources and residential consumers is considered. The load pattern is given in the following table:

Hour	Active Load (kW)	Hour	Active Load (kW)
1	32.32	13	54.77
2	26.94	14	49.39
3	24.24	15	48.49
4	22.45	16	44.90
5	17.96	17	44.90
6	17.96	18	62.86
7	26.94	19	80.81
8	35.92	20	88.00
9	48.49	21	88.90
10	47.59	22	80.81
11	46.69	23	68.24
12	53.87	24	49.39

The following are examined :

1. There are no micro-sources, all the demand met by the grid. Calculated cost **60.13** Euro
2. Good Citizen Policy : Calculated cost **52.74** Euro or 12.29% cost reduction
3. Ideal Citizen Policy : Calculated cost **48.91** Euro or 18.66% cost reduction

The Income for the Aggregator of is 11.22€. In this case energy is sold to the grid for some hours, more specifically between the 11th and the 16th hour.

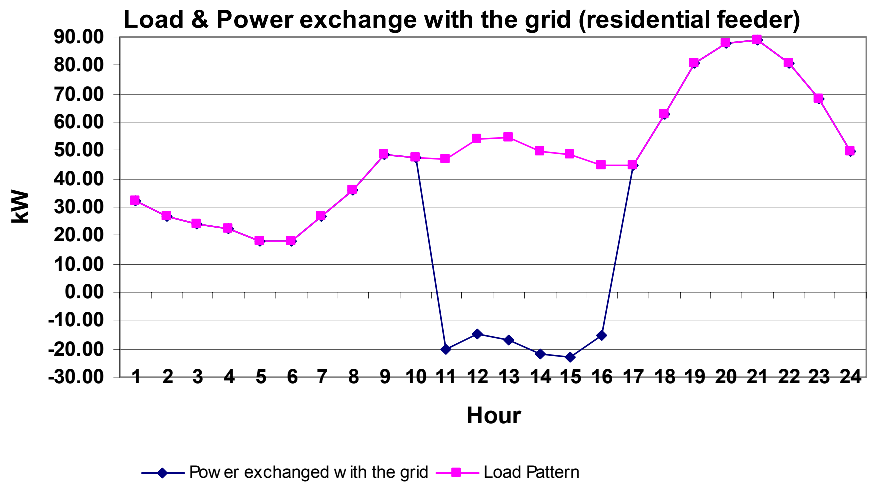


Figure 3.5.2. Load and Power Exchange for residential feeder market policy 2

Negative values mean export to the grid. It can be seen that for a few hours a day active power is sold to the grid. These examples show that the cost reduction in the ideal citizen policy is greater than in the first case**.**

	Study Case 1			Study Case 2		
Policy	**Grid only**	**Good Citizen**	**Ideal Citizen**	**Grid only**	**Good Citizen**	**Ideal Citizen**
Cost(€)	177.17	165.4	165.4	60.13	52.74	48.91
Energy Cost **(€ct/Kwh)**	5.73	5.35	5.35	5.17	4.53	4.21
Cost Reduction(%)	0%	6.6%	6.6%	0%	12.29%	18.66%

3.6 Environmental benefits

In order to evaluate the environmental benefits of Microgrids, the emissions from the operation of the central generation feeding the main grid should be compared to the emissions of the micro-sources. The emissions of the following are calculated: CO_2 , SO_2, NO_X and Particulate Matter

3.6.1 Emissions from the main grid

The production of the microsources displaces power from the main grid. Thus, the emissions avoided are approximately the average value of the main grid emissions per kWh multiplied by the production of the microsources. Indicatively, typical values of emissions from the Greek Mainland system ae shown in the following Table.

Pollutants	gr/kWh
CO_2	889
SO_2	1.8
NO_X	1.6
Particulate Matter	0.501

3.6.2 Emissions from the Microsources

Microsources, even the ones that consume fuel, have significantly lower emissions than central generation. Renewables, such as wind and solar based generation have zero emissions. It is assumed that the fuel burned by the Microturbines and the Fuel Cells is natural gas.
The following table gives typical emissions data
(http://www.epa.gov/globalwarming/greenhouse/greenhouse18/distributed.html
Emissions data from Joel Bluestein, Energy and Environmental Analysis, Inc.)
Emissions from gas-fired engine assume a rich-burn engine with a three-way catalyst.

UnitName	CO2_coeff(gr/Kwh)	NOX_coeff(gr/kWh)	SO2_coeff(gr/kWh)	Particulate Matter (gr/Kwh)
Microturbine	724.6	0.2	0.004	0.041
FuelCell	489	0.01	0.003	0.001
Wind1	0	0	0	0
PV1	0	0	0	0
PV2	0	0	0	0
PV3	0	0	0	0
PV4	0	0	0	0
PV5	0	0	0	0

3.6.3 Indicative Results - Changes in cost and emissions avoided

For the study case network, if we assume that all micro-sources were committed so that CO_2 emissions are minimized, then the emissions avoided would be:

548 kg CO_2
2.36kgr NO_X
2.812 kgr SO_2
756 g Particulate Matter

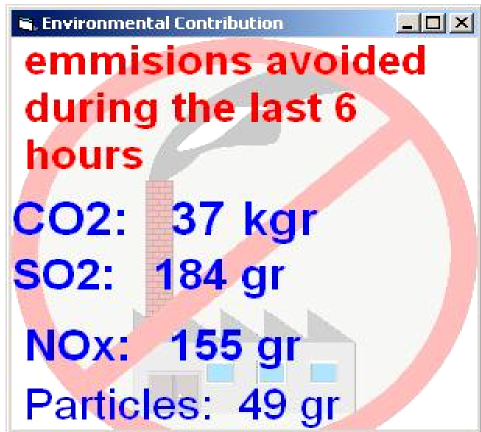
The cost for the whole period would be 216.34 € compared to 177.17 € of the solution without having any micro-sources committed. This is a 22.11% higher cost .

Compared to committing the micro-sources according to good and ideal citizen policies, the cost is higher by 30.4% and the emissions avoided would be:

148 kg CO_2
736 g NO_X
620 gr SO_2
196 g Particulate Matter

This means that the CO_2 emissions avoided are reduced by 73% .

In the software developed, emissions avoided are displayed as follows:



3.6.1 Emissions avoided by the Microgrid proposed operation

4. DYNAMIC SECURITY ASSESSMENT

4.1 Introduction

For microgrid operation, dynamic security assessment provides a way to evaluate the robustness of the LV microgrid to survive to a sudden disconnection from the MV network. Such a sudden change on the system's operating conditions must be quickly and efficiently compensated by the microsources in order to avoid large frequency excursions, which may trigger the existing frequency relays, causing the system to collapse.
Since dynamic the microgrid behavior analysis is a complex and computational burden task, this evaluation is performed exploiting functional knowledge, generated off-line, and using machine learning techniques.
The generation of functional knowledge (learning set generation) requires the analysis of the dynamic behaviour of the microsources operating together in the Low Voltage (LV) network under several different predetermined operating conditions, for the situation - passage to islanding operating mode i.e. disconnection from the upstream Medium Voltage (MV) network.
The degree of robustness of the system will be evaluated by estimating the maximum frequency deviation the microgrid will experience following the considered disturbance. No other disturbances are considered at this stage.
In order to generate a representative learning set, a large number of dynamic simulations are required in order to generate a sufficient amount of data to cover the set of possible operation points (different scenarios of load and distributed generation) for the microgrid. For each operating condition the security index – maximum deviation in frequency – is evaluated and kept. The dynamic simulations were performed using the simulation platform under the MatLab® Simulink® environment developed for the tasks in Work Package D and described in [1]-[2], with slight modifications introduced in the control of the microturbines.

The models of the microsources included in the simulation are described in the Deliverable DA1 [1], with some modifications included in the latest Progress Report for Work Package D [2]. Only three-phase balanced operation of the network is considered.

4.2 Objectives

The main goal of this analysis is to evaluate and, if possible, to predict the preservation of a safe operating mode based on a determined set of conditions of the various microsources and loads in the LV network (different operating scenarios). This analysis will hopefully provide (in an operational time basis) valuable information about the robustness of the microgrid, allowing the central controller to define a more robust operation strategy to guarantee that, under a determined set of conditions, the moving from interconnected operation mode to islanding operation mode can be done safely – without large deviations in frequency.

The security index evaluation is performed through a Neural Network (NN), previously designed exploiting the information available in the learning set.

4.3 Adopted Procedure

The development and implementation of the NN, required the following stages:

- Initial selection of system variables to be used for characterization purposes;

- generation of a learning set;
- design of the NN, able to emulate with quality the frequency deviation index, which requires namely the definition of its architecture as well as the relevant input variables;
- performance evaluation (done using a test set data).

At present the electrical variables that were collected to characterize the operating conditions were:
- total load consumption level - PL;
- active power output of each microsource - Pgi;
- imported (or exported) power - Pimp;
- node voltages where the microturbines, the fuel-cell and the diesel group are connected - Vi.

The learning set generation involved the following stages:
- definition of a set of scenarios with different operating conditions (load levels and microsources generation levels)
- Simulation of moving to islanding operation in each of the scenarios created and collection of a set of variables to be used in the next steps;

For this purpose, a large number of scenarios exploring a wide variety of operation points must be used. About 1600 were generated for training the NN and for performance evaluation purposes. These scenarios are built considering a certain number of levels of production from each microsource and a number of levels of total load.

Some scenarios were excluded in a preliminary phase for being unrealistic, namely those in which a large amount of power is exported by the microgrid to the upstream MV network. The set of operation scenarios simulated included combinations satisfying the previous constraint taking into consideration:

- Load variation from 25 % to 100% of the maximum load, in small steps;
- Split-shaft microturbine output powers: [0*, 27] kW, in small steps;
- Single-shaft microturbine output powers: [8, 27] kW, in small steps;
- Diesel group output powers: [10, 20] kW, in small steps;
- SOFC output powers: [7, 28] kW, in small steps;
- Wind generator output powers: [0*, 15] kW, in small steps;
- PV output powers: [5, 10] kW, in small steps;

[*] Some scenarios were considered with the Split-shaft microturbine and the Wind generator disconnected from the microgrid.

After generating the data, 1/3 of these operating points were separated from the initial set for performance evaluation purposes leading to a test set.

4.4 NN Results

The operating points of the learning set were used to design a NN that emulates the expect frequency deviation the system will present for the given operating conditions and for the disturbance under consideration – moving to islanding mode.

The design of the NN was preceded by an initial stage where an identification and selection of the most relevant variables was performed. This involved namely correlation statistical analysis.

Several tests were performed to select the appropriate variables and define the NN architecture.

The best performance was obtained using the following variables as inputs of the NN:

- Diesel group active power;
- Split-shaft microturbine active power;
- Single-shaft microturbine active power;
- Imported (or exported) active power;
- Active load in the microgrid;
- SOFC reactive power;
- Imported (or exported) reactive power;
- Reactive load in the microgrid;
- Node voltage where the Single-shaft microturbine is connected;

The feed-forward NN architecture that was adopted has the following characteristics:

- An input layer with 9 neurons and a hyperbolic tangent activation function;
- A hidden layer with 10 neurons and a hyperbolic tangent activation function;
- An output layer with 1 neuron and a linear activation function;

The training approach was based on a backpropagation approach.

An evaluation of the quality of the NN was performed afterwards using the test set. The results obtained are presented next.

Figure 1 shows the Mean Square Error (MSE) in the train and test sets during the learning stage procedure and Figure 2 shows the data fitness quality in the NN (the real frequency deviations – target values - are compared regarding the emulated ones).

The results obtained indicate that the selected variables are sufficient to emulate the index used to characterize the robustness of the microgrid operation. The architecture used proved to be adequate to accomplish the proposed objective.

Mean Square Error	0.000125
Mean Absolute Error	0.0065

Table 1: Performance evaluation results

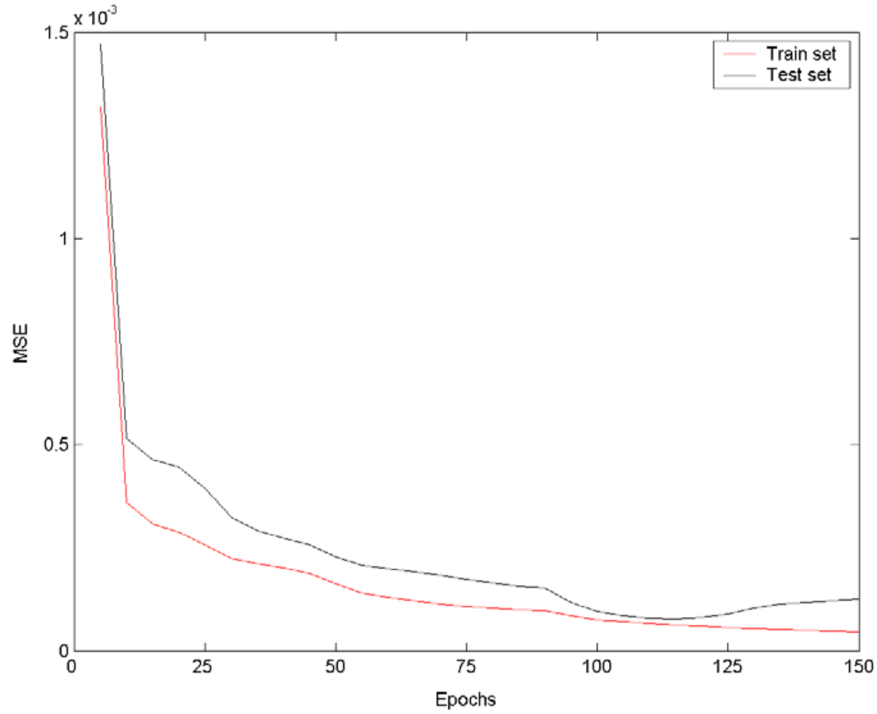


Figure 4.1: Train and test sets MSE

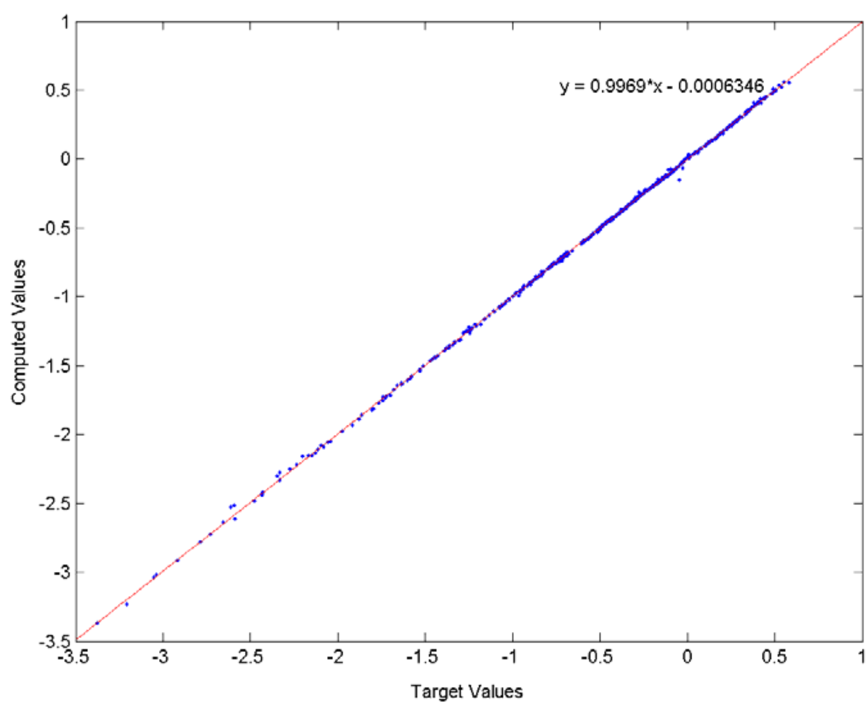


Figure 4.2: NN performance

From the observation of Figure 4.2 one can see the quality of the NN emulation capability. The emulated values are very near to the target one obtained through numerical simulation.

4.5 Conclusions regarding application of NNs

An evaluation of the dynamic robustness of the microgrid was obtained through the evaluation of the expected frequency deviation that the microgrid may experiment when moving to islanding operating conditions.

In order to obtain a fast evaluation of the robustness index a machine learning approach was adopted – in this case a Neural Network was designed for this specific purpose. With this NN it is possible to provide at the MGCC a very fast and accurate evaluation of the degree of robustness of the microgrid that may help managing the microsources production level.

Further results regarding the capability of the NN to deal with more scenarios will be included in Deliverable "***DC2. Description and Evaluation of Microgrid Controller Strategies***". This can be done by increasing the diversity of operating conditions to be considered during the learning set generation stage.

4.6 Application of Decision Trees

The following sections describe the application of Decision Trees for the extraction of security assessment structures. A small theoretical description of decision trees is presented in the next Section. A more detailed description can be found in [3] and [4].

4.6.1 The Tree-Building Algorithm

The tree-building algorithm is presented in the next figure. Each part is analysed next.

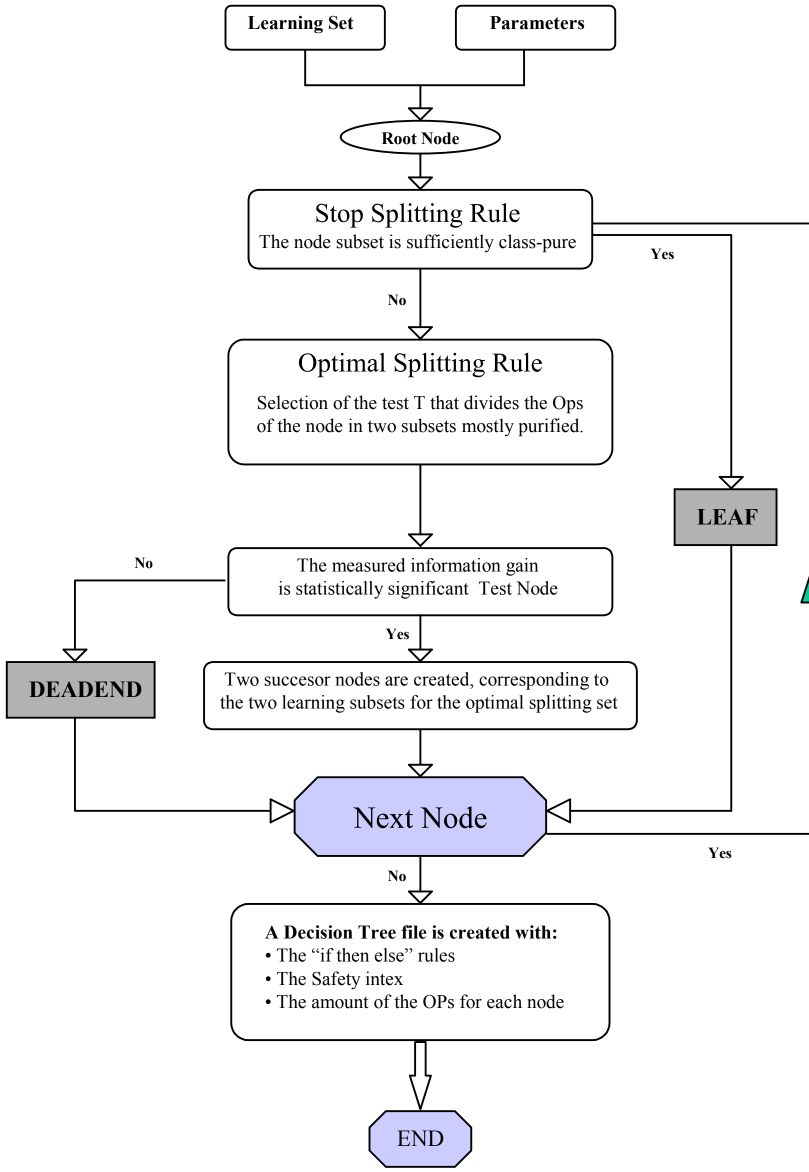


Figure 4.3 Procedure of decision trees construction

The construction of a DT starts at the root node with the whole LS of pre-classified OPs. These OPs are analysed in order to select the test that splits them "optimally" into a number of most "purified" subsets, which correspond to the successor nodes. For the sake of simplicity, a 2-class partition is considered in the following analysis, i.e. each OP is characterized either as SAFE or as UNSAFE. The selection of the optimal test is based on maximizing the additional information gained through that test. A measure of the information provided by a test is based on the entropy of the examined subset. This procedure, known as the **optimal splitting rule**, is applied recursively to each new node, to build the corresponding subtrees.

In order to detect if a node is terminal, i.e. sufficiently "class-pure", the **stop splitting rule** is used, which compares the classification entropy of the node with a minimum preset value H_{min}. If it is lower than H_{min}, then the node is sufficiently class-pure and it is not further split. Such nodes are labelled LEAVES. Otherwise, a suitable test is sought to divide the node, by applying the optimal splitting rule. In the case that no test can be found with

statistically *significant* information gain, the node is declared a DEADEND and it is not split. In the following, the basic terms involved in the tree-building procedure are introduced and the algorithm is explained in more detail.
Each node possesses a subset of OPs with the following characteristics:

E_n : the OPs subset of node n of the DT.
N : size (number of OPs) of E_n.
n_s : number of safe OPs in E_n.
n_u : number of unsafe OPs in E_n.

The relative frequencies of safe and unsafe OPs for node n will be:

$$f_s = \frac{n_s}{n_s + n_u} = \frac{n_s}{N} \quad \text{and} \quad f_u = \frac{n_u}{n_s + n_u} = \frac{n_u}{N}$$

The entropy of E_n with respect to the class partition of its elements, is defined as

$$H_c(E_n) = -(f_s \log f_s + f_u \log f_u)$$

where all logarithms are based on 2. $H_c(E_n)$ is a measure of the class-purity of the node subset E_n and, consequently, of the uncertainty of the classification of a state by this node. The following relations hold for $H_c(E_n)$:

$$0 \le H_c(E_n) \le 1$$

$$H_c(E_n) = 0 \Leftrightarrow (f_s = 1 \text{ or } f_u = 1)$$

$$H_c(E_n) = 1 \Leftrightarrow f_s = f_u = 0.5$$

A test T is defined at node n as:

$$T : A_i \le t$$

where A_i is the value of attribute i of a particular OP and
t a threshold value
By applying the test T to all OPs of node n, E_n is split into two subsets E_{n1} and E_{n2}:

$$E_{n1} = \{ OPs \in E_n : A_i \le t \}$$

$$E_{n2} = \{ OPs \in E_n : A_i > t \}$$

If n_i : number of OPs in E_{ni}, i=1,2
n_{si} : number of safe OPs in E_{ni}, i=1,2
n_{ui} : number of unsafe OPs in E_{ni}, i=1,2
then the corresponding frequencies are given by

$$f_1 = \frac{n_1}{n_1 + n_2} = \frac{n_1}{N} \quad \text{and} \quad f_2 = \frac{n_2}{n_1 + n_2} = \frac{n_2}{N}$$

$$f_{s1} = \frac{n_{s1}}{n_{s1} + n_{u1}} = \frac{n_{s1}}{n_1} \quad \text{and} \quad f_{u1} = \frac{n_{u1}}{n_{s1} + n_{u1}} = \frac{n_{u1}}{n_1}$$

$$f_{s2} = \frac{n_{s2}}{n_{s2} + n_{u2}} = \frac{n_{s2}}{n_2} \quad \text{and} \quad f_{u2} = \frac{n_{u2}}{n_{s2} + n_{u2}} = \frac{n_{u2}}{n_2}$$

The entropy of E_n with respect to the partition induced by T is

$$H_T(E_n) = -(f_1 \log f_1 + f_2 \log f_2)$$

$H_T(E_n)$ is a measure of the uncertainty of the outcome of test T and has similar properties with $H_c(E_n)$:

$$0 \leq H_T(E_n) \leq 1$$
$$H_T(E_n) = 0 \Leftrightarrow (f_1 = 1 \text{ or } f_2 = 1)$$
$$H_T(E_n) = 1 \Leftrightarrow f_1 = f_2 = 0.5$$

The mean conditional entropy of E_n, given the outcome of test T, corresponds to the residual entropy after the application of T and is defined as

$$H_c(E_n|T) = f_1 H_c(E_{n1}) + f_2 H_c(E_{n2})$$

The information gained from the application of test T is expressed by the achieved reduction of the learning subset entropy:

$$I(E_n;T) = H_c(E_n) - H_c(E_n|T)$$

The following relation holds

$$0 \leq H_c(E_n|T) \leq H_c(E_n) \Leftrightarrow 0 \leq I(E_n;T) \leq H_c(E_n)$$

A more objective (less biased) estimator of the merit of test T is provided by the normalised information gain, defined as

$$C(E_n;T) = \frac{2I(E_n;T)}{H_c(E_n) + H_T(E_n)} \in [0,1]$$

For each node of the DT, the optimal splitting rule consists of selecting the test that minimises the classification uncertainty, i.e. the one with the highest information gain C(En;T). However, the learning set and each of its subsets En are only statistical samples of the Universe U (resp. Un) of the operating points of the system. In the same way, the subsets En1 and En2 are samples of the corresponding partitions Un1 and Un2 of Un, obtained through T. Hence the frequencies of safe and unsafe OPs in En, fs and fu, are estimators of the actual probabilities, ps and pu, of an OP in Un being respectively safe or unsafe. Similarly, the frequencies f1 and f2 of the OPs in En which conform or not to the test T are estimates of the corresponding actual probabilities, p1 and p2. The same holds for the various entropies and information measures defined by the previous relations.

Although the calculated frequencies are generally unbiased, the information measures derived by them are rather optimistically biased, over-estimating the merit of the examined test. As it is expected, the amount of bias is inversely proportional to the number of learning states (OPs), i.e. to the representativity of the considered learning subset. In order to detect whether the calculated information gain for each test reflects an actual increase in information from the application of test T to unforeseen OPs or it is simply apparent (i.e. a random effect, due to the limited size of the sample), suitable statistical hypothesis tests are used, as the ones discussed in the Appendices A and B.

The steps followed by the tree-building algorithm are summarized in the following:
1. The procedure starts from the top node with the whole LS.
2. It is examined if the node should be further split by applying the stop splitting rule:
   - If the node subset is sufficiently class-pure ⇒ LEAF
   - If not ⇒ Proceed to Step 3.
3. Selection of the optimal splitting test (Optimal splitting rule)
   - Selection of the test T that divides the OPs of the node in two subsets mostly purified.
4. Statistical significance testing of the optimal test.
   - If the measured information gain is statistically significant ⇒ Test Node. Proceed to Step 5.
   - If there is no statistically significant way to expand the node ⇒ DEADEND

5. Splitting of the node
    - Two successor nodes are created, corresponding to the two learning subsets for the optimal splitting test.
6. Steps 2-5 are recursively applied to the successor nodes.

The Optimal and Stop Splitting rules consist of the following actions:

Optimal Splitting Rule

- For each candidate attribute A_i (i=1..N) find the optimal threshold value a_i*, so that the corresponding test
$$T_i^*: A_i \leq a_i^*$$
provides the maximum (*statistically significant*) information gain
$$C_i^* = C(T_i^*)$$

- Select the optimal test T* among the T_i* (i=1..N), which provides the maximum increase in information:
$$C^* = \max_{i=1..N}(C_i^*)$$

- Split the node in two successors using the optimal test T*.

Stop Splitting Rule

- If $H_C(E_n) < H_{min}$ the node subset is sufficiently class-pure ⇒ LEAF
Otherwise use the Optimal Splitting Rule to split it.
- If the node cannot be split in a statistically significant way ⇒ DEADEND

The **parameters** involved in the tree-building algorithm are:

- H_{min}: The minimum node entropy, below which the node is declared a Leaf.
- X^2-test: Type of statistical hypothesis test used.
- á : The assumed risk level.

4.6.2 Performance Evaluation of the DTs

The accuracy or reliability of the developed DTs is tested using a set of preclassified OPs, called the Test Set (TS), which is similar in nature with the LS. The states of the TS are reclassified by the DT and the *a posteriori* classification results are compared with the *a priori* classification of the OPs, in order to determine the success and error rates.

The most important evaluator of the DT reliability and performance is the rate of successful classifications, defined as the ratio of successfully classified OPs to the total number of OPs tested:
$$\text{Success Rate} = \frac{\text{OPs successfully classified by the DT}}{\text{Total number of OPs in the TS}}$$

For a bi-class partition (Safe-Unsafe) there can be distinguished two types of error, depending on the actual class of the misclassified OP:

$$\text{False Alarm Rate} = \frac{\text{Safe OPs misclassified as Unsafe by the DT}}{\text{Total number of Safe OPs in the TS}}$$

$$\text{Missed Alarm Rate} = \frac{\text{Unsafe OPs misclassified as Safe by the DT}}{\text{Total number of Unsafe OPs in the TS}}$$

There is also defined the **Global Error** rate, as:

$$\text{Global Error rate} = 1 - \text{Success Rate}$$

4.7. DT Results

An indicative DT satisfying the following **security criterion** is shown in Figure 4.4:

If *fmin* < 49 Hz **or**
V Bus3<390V **or** *V Bus 4<390V* **or** *V Bus 8<390V* **or** *V Bus 9<390V* **then**
the system is insecure **else** is secure

In the upper right side of each node the number of the node is shown. In the upper left side is the percentage of the OPs that fall in the node. In the middle is either the separation criteria of the node or if the node is deadend or leaf. In case the separation test is true, we follow the left node, otherwise we go on the right. Finally in the bottom is the safety index, which is the safe OPs of the node divided to the total OPs of the node. A small number shows that most of the OPs are insecure, while a large one indicates that most of the OPs are secure.

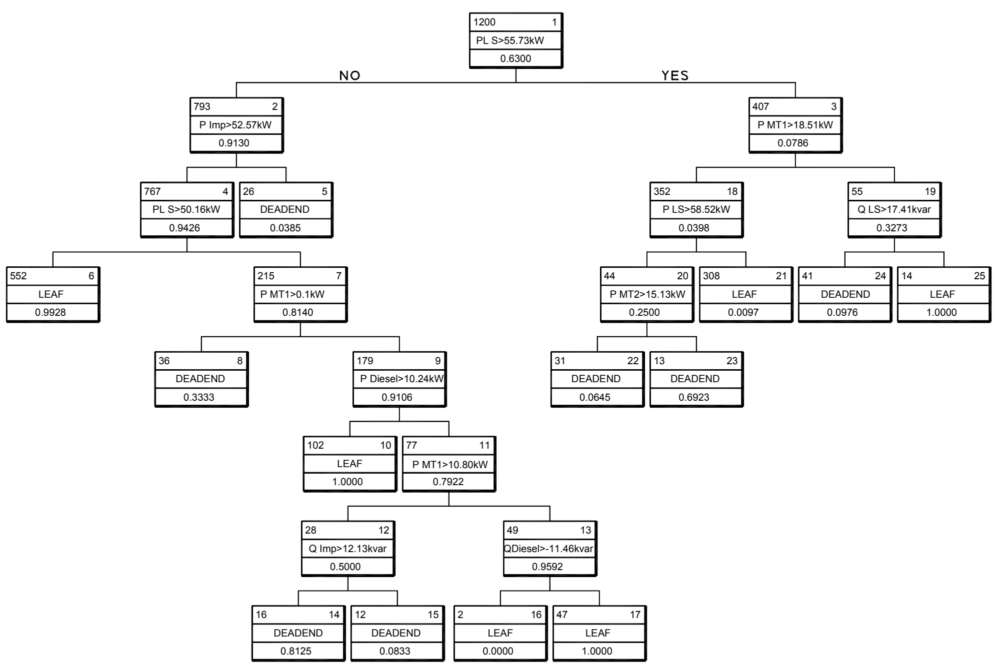


Figure 4.4 Decision Tree for Microgrid secure operation during interconnection loss

Attributes selected: variables 1 – 17

1. **P Diesel** – Active power in the diesel group
2. **P MT1** – Active power in the split-shaft microturbine
3. **P MT2 –** Active power in the single-shaft microturbine
4. **P SOFC –** Active power in the fuel-cell

5. **P Wind –** Active power in the wind generator
6. **P PV –** Active power in the PV
7. **P Imp –** Active power imported (if positive) or exported (if negative) from / to the upstream medium voltage network
8. **P LS –** Maximum active power available for load-shedding
9. **P Load –** Active load of the microgrid
10. **Q Diesel** – Reactive power in the diesel group
11. **Q MT1** – Reactive power in the split-shaft microturbine
12. **Q MT2** – Reactive power in the single-shaft microturbine
13. **Q SOFC –** Reactive power in the fuel-cell
14. **Q Wind –** Reactive power in the wind generator
15. **Q Imp –** Reactive power imported (if positive) or exported (if negative) from / to the upstream medium voltage network
16. **Q LS –** Maximum reactive power available for load-shedding
17. **Q Load –** Reactive load of the microgrid
18. **V Bus3 -** Line-line voltage in the bus where the diesel group is connected
19. **V Bus4 -** Line-line voltage in the bus where MT1 is connected
20. **V Bus8 -** Line-line voltage in the bus where MT2 is connected
21. **V Bus9 -** Line-line voltage in the bus where SOFC is connected
22. **Frequency Deviation –** maximum frequency deviation after moving to islanding operation (f_{max} – 50)

Evaluation of Decision Tree Performance

Classification Performance Evaluation				
	Learning Set		**Test Set**	
	LS 1200 OPs		TS 434 OPs	
	Secure	Insecure	Secure	Insecure
	756 OPs	444 OPs	291 OPs	143 OPs
Global Error	2.83% (44 OPs)		3.69% (16 OPs)	
False Alarm	3.04% (23 OPs)		3.45% (10 OPs)	
Missed Alarm	2.48% (11 OPs)		4.17% (6 OPs)	

4.8 Conclusions regarding application of DTs

The DT structures can be easily translated in a number of if…then…else rules that can be used on-line to assess the dynamic security of the microgrid, in case of loss of the interconnection or they can be used as dynamic security constraints in the optimization functions [5], [6].

Further results regarding the applicability of the DTs in on-line Dynamic Security assessment of Microgrids will be included in Deliverable "***DC2. Description and Evaluation of Microgrid Controller Strategies***".

4.9 References

[1] Kariniotakis, G.; et al, DA1 – Digital Models for Microsources, MicroGrids project deliverable of task DA1, July 2003

[2] Lopes, J. A. Peças; Moreira, Carlos; Gil, Nuno; Madureira, André – Progress Report for Work Package D – Task D1, MicroGrids project deliverable, April 2004

[3] L. Wehenkel and M. Pavella, "Decision tree approach to power system security assessment", Int. J. Electrical Power and Energy Systems, Vol. 15, No. 1, Feb 1993.

[4] L. Wehenkel, "Automatic Learning Techniques in Power Systems", Kluwer A.P., 1998.

[5] Hatziargyriou, N.D.; Papadopoulos, M.P.; Papathanassiou, S.A.; "Decision trees for fast security assessment of autonomous power systems with a large penetration from renewables", IEEE Transactions on Energy Conversion, Volume: 10 Issue: 2, Jun 1995, Page(s): 315 –325.

[6] Hatziargyriou, N.D.; Karapidakis, E.S., "Online preventive dynamic security of isolated power systems using decision trees" Power Systems, IEEE Transactions on, Volume: 17 Issue: 2, May 2002, Pp: 297 –304.

5. FORECASTING

"Prediction is very difficult, especially about the future", Niels Bohr, Nobel Prize in Physics 1922.

5.1 Introduction

As seen in the previous Sections where the various management functions were described, the MGCC needs to take several decisions for the next few hours based on what is the expected power demand, electricity prices, generation from the renewable power sources and heat demand.

Forecasting the evolution for these quantities permits to anticipate unsafe situations, to optimize production costs and in general to maximize revenues of the production process in the marketplace. As a consequence, forecasting options may have a direct impact on the economic viability of the microgrids option since they permit to enhance the competitiveness of this option compared to centralized generation.

The aim of this Section is to introduce the problem of short-term forecasting in the frame of microgrids and present the requirements for research. Such requirements are recognized today by the scientific community working on microgrids and DG as one of the research gaps in the area [1], **[7**]. Initially, some issues that are expected to be important when "forecasting" in microgrids are discussed. Then, example methods for forecasting the various quantities are given. It is premature to propose some operational forecasting tool for microgrids. Microgrids is an option for the future and several uncertainties exist regarding their development. For developing operational tools, a higher insight is required for the role of forecasting functionalities in microgrids. This insight can be gained in the frame of this project but also future projects by considering data from real case-studies, and by specifying in detail the management functions required for microgrids. The successful deployment of microgrids will depend however to the capacity of project such the present one to provide efficient solutions for all the required functionalities.

5.2 Are forecasting functionalities relevant for microgrids?

Depending on the mode of operation of a microgrid it is clear that in an isolated mode prediction of demand is of primary importance since the aim is to achieve the balance of the system. In a non-isolated mode the importance of predicting the demand or the generation may change if one considers a system-driven or a customer-driven approach. In the first case, forecasting functions may have less importance since one may consider that a microgrid after all is connected to an "infinite" source of power able to cover any deficit at any moment. In a customer-driven approach economics and thus forecasting gain in importance. Then, if the microgrids is the "business-case" i.e. of an energy service provider who has to consider electricity prices, then tool for taking decisions based on forecasting will be needed. Forecasting functions are expected to gain in importance when one considers multi-microgrids scenarios.

In any case, in the scale of a microgrid, one should consider *cost effective* approaches for forecasting. Today forecasting technology is an expensive one and forecasting tools are not plug & play ones. Developing and implementing forecasting options for a power system application involves costs for research & studies, instrumentation for data collection, operational costs for numerical weather predictions etc. Forecasting today has a price, which should be compared to the benefits it can bring. On the other hand, decentralizing power generation, especially by adding renewables, adds intermittence in the whole power generation process. Given that no compromise is expected for the quality of service, forecasting remains the principal cost-effective solution to fight against intermittence. One should not neglect *acceptability* of power system operators who so far had to manage almost deterministic processes (i.e. they are able, even without mathematical tools, to forecast the power system load with an impressive accuracy rising up to 1%). The capacity to accept more intermittent options is linked to the capacity to provide tools to compensate intermittence and manage uncertainties. This is especially true if one has to consider electricity market conditions where penalties are associated to uncertainties and decisions have to be taken as a function of the prices in the near future.

Considerable work in the power systems area has been devoted on forecasting demand, wind power, heat demand and recently electricity prices. This work however concerns large interconnected systems with a time scale and resolution that is not appropriate when someone goes down to the scale of microgrids. Less experience is available on forecasting with a high temporal resolution (i.e. 10 minutes) and for the next 1-4 hours. For this reason in very small applications usually persistence is applied. This is a simple method saying that the predicted variable will remain at the same value as it is now during the next period:

$$\hat{P}(t+k) = P(t), \quad \text{k=1,2,}\ldots n$$

This can be the base-line model for any process (load, heat, PV, wind, prices etc) considered by the management functions. Considering this model for taking decisions may penalize the benefits especially in the case of an electricity market where prices may be volatile. For evaluating the value of prediction one should simulate the operation of a microgrid using persistence forecasting against prefect forecasting. The difference between the two may indicate what is the interest to invest into advanced forecasting methods. Results from such as study would be however difficult to generalize since they would depend a lot on the structure of the microgrid, which can be quite variable, and also on the characteristics of the market (in some countries the balancing mechanism is more or less "favorable" to intermittent sources). As a conclusion it is emphasized the importance to develop methodologies and assumptions for monetizing the benefits from forecasting.

5.3 Predicting Demand in microgrids

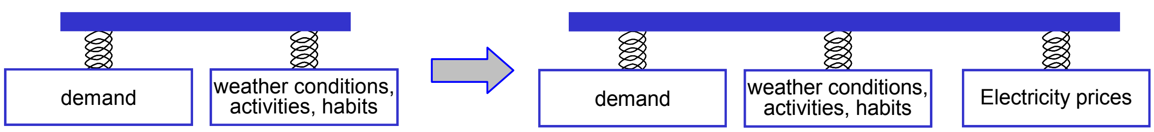
In the classical load-forecasting problem in interconnected or even autonomous power systems, demand depends on weather conditions, habits of the customers and activities. Due to these last two factors it is highly correlated to the hour and type of the day or season of the year. Predictions are usually required for the next 24/48 hours with hourly or 30-minutes time steps. The forecasting accuracy is high, that is in the order of 1-5 % depending on the time horizon and the type/size of the system. Uncertainty can be estimated by classical methods, such as resampling. In fact these forecasts can be provided with a high level of confidence. A large number of references and models exist for this type of load forecasting. An extended recent review focusing on artificial intelligence based techniques is given in [2].

If someone wishes to downscale the problem to small power systems such as the systems of islands then very few results are reported in the literature with the main ones being produced in the Care and More-Care projects by Armines and RAL. In these cases it was concluded that although the variability of load starts to increase, the predictability remains at high levels compared to the classical case. In these cases methods such as (fuzzy) neural networks have given good results [3]. Some recent publications [4], [5] give results in the very short-term but for large systems where intermittence however remains reduced due to the smoothing effect.

When however downscaling the demand prediction problem to the level of a microgrid, then situation is expected to change significantly. The aggregation or smoothing effect is reduced and uncertainty increases as the size of the microgrid gets smaller. On this difficulty one should add the increase in time resolution. We enter then the area of very short-term forecasting with reduced smoothing effects. Today there is a difficulty to find data from real cases to characterize adequately the problem.

The shortest time resolution for load forecasting that could be efficient to implement could not be less than 10 minutes if one would like to speak about large-scale applications. This corresponds to load following type of functions. The load following patterns of individual customers are highly correlated with each other. Load following changes are often predictable (e.g., because of the weather dependence of many loads) and have similar day-to-day patterns which can be captured with short term forecasting techniques.

In contrast to the classical load forecasting problem, it is expected also that the demand will be correlated to electricity prices. Prediction models for demand may consider as input (predictions) of electricity prices to accommodate this correlation.



To date, load has not been able to respond to price because the communication and market systems did not exist. The market signals may be handled in the future over the internet. The local system operator would have a statistical understanding of the demand response, and would be able to forecast his load accurately. This capability is one of the key attributes for the distribution system of the future.

In the frame of microgrids project the generic adaptive fuzzy neural networks model is applied as a base-line advanced model. This option is an appropriate one for research purposes since it provides the flexibility to consider various input variables according to the availability of data.

5.4 General presentation of the fuzzy neural network model.

The fuzzy model can be expressed in the form of rules of the type:

$$\text{"IF } \underline{x} \text{ is } A \text{ THEN } y \text{ is } B\text{"}$$

where $\underline{x}$, y are linguistic variables and A, B are fuzzy sets. Tagaki and Sugeno have proposed an alternative type of fuzzy rule [3]:

$$R: \quad \text{IF} \quad x_1 \text{ is } A_1, \text{ and } \ldots, \text{ and } x_n \text{ is } A_n \quad \text{THEN} \quad y = g(x_1, \ldots, x_n)$$

where :

$x_1,\ldots,x_n$ are real-valued variables representing input variables of the system defined in the universes of discourse $X_1,\ldots,X_n$ respectively. The particularity of the above rule is that input variables appear also in the conclusion.

$A_1,\ldots,A_n$ are fuzzy sets.

Y is variable of the consequence whose value is inferred.

g is a function that implies the value of y when $x_1,\ldots,x_n$ satisfy the premise. The function $g(.)$ in the consequent part of the rules may be a linear or a non-linear one or even a constant. In the case of a linear function the fuzzy rule base takes the form :

$$\begin{array}{llll} R^1: & \text{IF} \quad x_1 \text{ is } A_1^1,\ldots, \text{ and } x_n \text{ is } A_n^1 & \text{THEN} & y^1 = p_0^1 + p_1^1 x_1 + \ldots + p_n^1 x_n \\ \vdots & & \vdots & \\ R^m: & \text{IF} \quad x_1 \text{ is } A_1^m,\ldots, \text{ and } x_n \text{ is } A_n^m & \text{THEN} & y^m = p_0^m + p_1^m x_1 + \ldots + p_n^m x_n \end{array}$$

For the purpose of timeseries prediction, each variable x_i in the premises may correspond to a past value of the process (i.e. power: P(t), P(t-1)…), or past values of explanatory variables: (i.e. wind speed : WS(t), WS(t-1)…) or meteorological forecasts (WS_m(t+1), WS_m(t+2), …).

A linear function in the consequence is indeed an ARX (autoregressive with exogenous variables) model. It is clear that with the above definitions, the rule base consists of an ensemble of “local” models. Such local modelling is a desired property of the model especially in the case of a non-stationary process such as wind production.

Fuzzy sets in the premises are modelled here using Gaussian functions:

$$\mu_{A_j^i}(x_j) = \exp\left(-\left(\frac{x_j - a_j^i}{b_j^i}\right)^2\right)$$

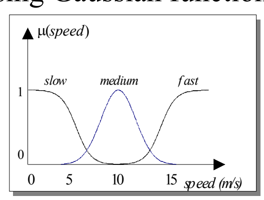


Figure 1: *Representation of fuzzy wind speeds. "Speed" is a linguistic variable with three terms "slow", "medium", and "fast" represented as fuzzy sets with the membership functions shown in the Figure.*

The output of the model y_i represents the predicted process, i.e. demand or wind power $\left(\hat{P}(t+1), \hat{P}(t+2), \ldots\right)$

The model may be written in an analytical form as following:

$$\hat{y} = \frac{\sum_{i=1}^{r}\left(p_0^i + \sum_{j=1}^{m} p_j^i x_j\right) \cdot \prod_{j=1}^{m} \mu_{A_j^i}(x_j)}{\sum_{i=1}^{r} \prod_{j=1}^{m} \mu_{A_j^i}(x_j)} \hat{=} \sum_{i=1}^{r} w^i \hat{y}^i$$

A simpler model consists in a consequence part with a constant instead of a linear function. Appropriate learning rules are derived according to the stochastic gradient scheme to tune all the parameter of the model.

5.5 Contribution of weather predictions to operation at best efficiency point.

The consideration of weather forecasts as a general input to the various forecasting functions in the MGCC seems to be an option that may be exploited in a multiple way. Apart from their use for reliable forecasting of renewable units production and power demand, their role can be also important in case that micro turbines are present for operating at their best efficiency points. This aspect may gain importance also in larger scale systems or multi-microgrid systems. For light load conditions, it would be better to have fewer microturbines running, but running at rated load, than to have several microturbines running at partial load. This is because the microturbines are more efficient when operating at rated load. The decision of how many machines to run, and at what load, can best be made by the MGCC, because it has knowledge of the process condition, the weather forecast, and the production schedule. This requirement is also identified in **[6]** for EMS destined to microgrids.

5.6 Prediction of wind production

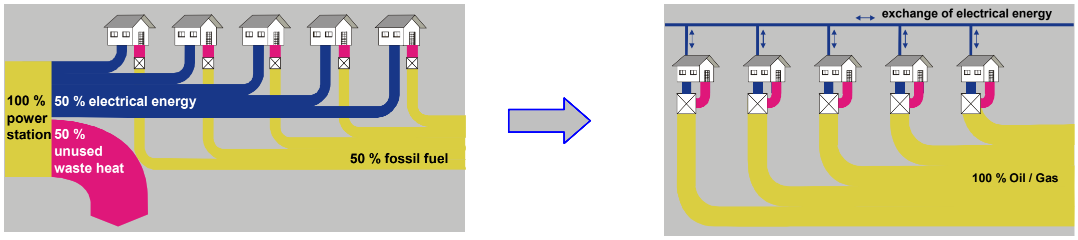
Microgrids are expected to be more developed in urban environments where the development of wind energy might not be welcome as a viable option. However, small wind turbines is still an option with a high potential in many cases. Short-term forecasting is of primary importance for integrating wind energy in a power system, especially at the transmission level. Research in wind forecasting is multidisciplinary since it combines meteorology, statistics, physical modeling, computational intelligence etc. Advances in this area are expected to benefit also other areas such as forecasting of PV, heat and hydro and also demand.

The main project in this domain today is ANEMOS (ENK5-CT-2002-00665) in which European institutes and end-users devote considerable efforts to improve the efficiency of the wind forecasting technology and to provide next generation tools. A description of the various research activities in this project is given in [8] together with a long list of produced papers in the project. At the same web site, a deliverable position paper with a detailed state of the art on wind power forecasting can be downloaded (more than 122 references analyzed) [9]. The intensive work in this project on a great number of test cases, onshore and offshore, shows that the problem of wind forecasting is far from trivial and that priority should be given in the next years in this area if one wants to enhance the competitiveness of wind energy in the market liberalization process and achieve large-scale wind integration.

In the case of very short-term wind power prediction a review of available models is given in [10]. If meteorological forecasts are not available then a model has to be based purely on past measurements. A fuzzy-neural networks based model as the one presented above can be adequate for this purpose.

5.7 Prediction of heat demand

One of the main motivations for developing distributed generation and especially the microgrids option is to achieve higher energy efficiency by combining heat and power demand covering.



Forecasting heat consumption is a necessary functionality that has to be provided to the MGCC for optimizing decisions on covering this demand. The heat demand main features are:

- time of day effect,
- weekend/weekday effect,
- seasonal effects,
- time varying volatility,
- high negative correlation between heat demand and outside temperature.

Several approaches have been developed so far for on-line prediction of heat consumption in district heating systems. The horizon is often 72 hours ahead and the time step is hourly. The simpler approaches are based on purely ARIMA models that use only heat demand data as input. SARIMA models considering seasonal differencing has been also applied. As an extension ARIMAX models are also considered with temperature as an explanatory variable.

More advanced developments assume that meteorological forecasts are available on-line. As explained above, such forecasts can be jointly used for forecasting the other quantities such as wind or solar generation etc. In the study developed by [11] it is reported a mean absolute relative prediction error for 72 hour predictions is 3.8% for data of an autumn month. This error increases up to 17% when no climate information is used. The relative prediction error tends to increase with decreasing heat consumption.

The methods of prediction applied are based on adaptive estimation that permits to adapt to slow changes in the system. This approach is also used to track the transition from e.g. warm to cold periods. Due to different preferences of the households to which the heat is supplied this transition is smooth.

The models developed in [11] are based on the so called gray box approach which combines theoretical knowledge about the system with information from measurements performed on the system in order to obtain a mathematical description. Furthermore it is also demonstrated that it is important to select the estimation method depending on the particular application.

Below a typical prediction non-casual model for heat consumption is given. Details on its development are provided in [11] :

$$Q_t = \mu\left(h_t^{24}, Y_t\right) + a_{20}H_2(q)R_t + a_{111}H_1(q)W_t + a_{120}H_1(q)T_{a,t} + a_{121}H_1(q)W_tH_1(q)T_{a,t} + \\ + a_{100}H_1(q)R_t + a_{101}H_1(q)W_tH_1(q)R_t + a_{211,0}W_t + a_{211,1}W_{t-1} + a_{220,0}T_{a,t} + a_{220,1}T_{a,t-1} + e_t$$

where $H_1(q) = \dfrac{0.066}{1 - 0.934q^{-1}}$ and $H_2(q) = \dfrac{-0.350 + 0.612q^{-1} - 0.226q^{-2}}{1 - 0.703q^{-1} + 0.793q^{-2}}$

in which :

Q_t : is the heat consumption at time t,
W_t : is the wind speed,
$T_{a,t}$: is the air temperature,
R_t : is the solar radiation,
a : are the parameters.

In [12] the following prediction simple linear prediction model is proposed:

$$Q_t = b_o + b_1 D_t + b_2 V_t + b_3 P_t + b T_t + b_5 H_t + b_6 S_t$$

where :

b_i : are the parameters
D_t : is wind direction
V_t : is wind speed
P_t : is atmospheric pressure
T_t : is the temperature
H_t : is humidity
S_t : is solar radiation.

In the above studies the authors show that the meteorological variables play an important role in the above models.

As an alternative one could consider black box models such as neural networks [13] or fuzzy logic neural networks similar to the one presented above. In this case more flexibility is gained regarding the structure of the model and the available information according to the application.

5.8 Prediction of electricity prices

Short-term forecasting of electricity prices may be of high importance as explained above especially in a volatile electricity market environment. Spot prices may significantly influence decisions on the use of microsources. Nowadays, various approaches have been tested for his purpose. Electricity prices vary from other commodities due to the fact that the primary good, electricity, can not be stored, implying that inventories can not be created and managed to arbitrage prices over time. As an example, the process in Leibzig Power Exchange can be characterized by the following futures [14], [15] :

- strong mean reversion: deviation of the price due to random effects are corrected to a certain degree.
- time of the day effect,
- calendar effects such as weekdays, weekends and holidays,
- seasonal effects,
- time varying volatility and volatility clustering
- high percentage of unusual prices mainly in periods of high demand,
- inverse leverage effect: a positive price shock has a bigger impact than a negative one.

- non-constant mean and variance

Some of the models that have been applied for short-term price forecasting include:

- mean reverting processes
- mean reverting processes with time-varying mean
- autoregressive moving average models (ARMA)
- exponential generalized autoregressive conditional heteroscedasticity models (EGARCH)

5.9 Evaluation of uncertainties on predictions

As analyzed above, in the case of microgrids the time resolution increases resulting to an increase of intermittence. On this should be added the downscaling compared to larger power systems and the reduced smoothing effect due to limited aggregation. In parallel to the research on forecasting models it is necessary to carry research and develop models for evaluating on-line the uncertainty of the predictions. For example, regarding wind power forecasting the existing operational tools are not able to provide intervals with a predefined level of confidence. The only formal approach for estimating confidence intervals appropriate to this problem (conditional probabilities, effect of power curve) has been developed recently in the frame of ANEMOS project [8]. The complete methodology is presented in detail in [16].

5.10 Conclusions

In the frame of microgrids, forecasting is important since it permits to optimize management and thus improve economics. Artificial intelligence techniques are promising together with other options so far developed. However, such options have to be validated with real data reflecting the situation in real microgrids. In the microgrid scale all forecasted processes are expected to be more intermittent than in larger power systems. For this reason, research for tools need to be developed for estimating on-line the uncertainty. The uncertainty itself needs to be quantified. Studying the predictability and the variability of the various processed related to microgrids is of major importance for deciding what kind of approaches are appropriate for the management functions (i.e. deterministic or probabilistic ones). Research has to be carried out towards the development of cost effective prediction tools with plug & play capabilities.

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6. DEMAND SIDE MANAGEMENT

6.1 System description

6.1.1 Introduction

In this section a centrally controlled demand side management system developed by Labein is presented. The system has been designed having in mind the particular nature of microgrids, but it can also be used by any distribution management system (DMS) controller that has the capability to control the load.
The operation of microgrids opens new perspectives to demand side management. Microgrids are low voltage grids with modular generation connected into them that can run connected or isolated from the main grid. Significant part of the generation connected into microgrids is expected to come from renewable energy resources. The unpredictability of the renewable sources makes the islanded operation and dispatch of microgrids challenging. In this situation the load control is very desirable and in some cases a real necessity. A common way to safely operate a small isolated microgrid where only renewable generation is available is to provide some storage, alternative generation and finally use distributed intelligent load controllers that shed loads in case of voltage and frequency excursions. The load control system that is presented in this document is centralised. It is based on the existence of a microgrid central controller that calculates suitable control actions and sends them to the loads.
The operation of microgrids requires two way communications between the central controller and the system elements (generators, storage devices, loads…). The designed DSM system will benefit from this communication infrastructure allowing a two way real time communication between the central controller and the controllable loads.

The microgrid central controller or the DMS controller has full information and knowledge of the managed network. It integrates load forecasting tools, weather forecasting tools, generation forecasting and knows the existing generation capacity, storage capacity, network topology, network constraints, losses, security requirements, market prices, bilateral contracts, etc., that is, it behaves as a traditional vertically integrated utility.
Based on this information the central controller decides which load would be desirable to be consumed in the following time period. The criteria for deciding the optimal load consumption can vary widely. The criteria could be to maximise the use of renewable energy resources, to maximise the economic benefit within the complete microgrid, to minimise the amount of power imported from the main grid, peak reduction, and so on.
The desirable load is usually calculated one day in advance. The central controller provides a curve: an objective load value for each time step (half an hour for example) of the next day.
The central controller calculates the aggregated amount of load that would be desirable to consume in the complete microgrid, or it could separate the network into different parts, using more complex algorithms that take network topology and loses into account and provide a different objective curve for each of the parts.
The demand side management system is not involved in the calculation of these objective load curves. The DSM system receives the objective load curves as an input and calculates the required load control actions in order to fulfil the desired load consumption. The system is flexible in the sense that it is completely independent from the criteria used to generate the objective load curve.

Labein's developed system runs two different load control algorithms. The first one delays loads from their expected connection instant to times that provide the smallest deviation between the objective load curve and the actual load consumption curve. The algorithm runs a quadratic program and finds the best possible load scheduling. The payback of the devices that are moved is considered to be 1. The shifting algorithm is run periodically (usually on a daily basis).
The second algorithm curtails load. Load curtailment is something that should only be executed under exceptional circumstances for system security. Drivers like maximisation of the use of renewables or maximisation of the economical profit within the microgrid hardly would bring a load to be tripped. In developed DSM system the load curtailment algorithm is run every time central controller requires. Central controller detects the need for load curtailment and sends a new objective load curve to the DSM system for a short time horizon. The load curtailment algorithm then calculates the required control actions that bring the actual load curve closest to the given objective load curve. Air conditioners are the devices that will mainly be targeted by the load curtailment algorithm.

Demand side management can also play a significant role on the liberalisation of electricity markets. If DSM system informs the microgrid central controller about the new load reschedule and the available load reduction capabilities for each time step of the next day, it could place bids in the market offering load reduction capacity.

The aim of the system that has been developed on this study is to build a general demand side management system capable of controlling most of the domestic devices and the commercial air conditioning at the same time. On the majority of the previous studies on direct load control, researchers focused on the control of a particular type of appliance, mainly water heaters or air conditioners. They came up with load control methodologies that considered in great detail the particularities of the device being controlled.
The methodology developed here controls many devices at the same time and the modelling of the behaviour of each device is not, in general, so detailed in terms of considering thermal behaviours, these aspects are assumed to be locally managed by the next generation of advanced intelligent devices.

6.1.2 Review of previous experiences

Over the last years there have been numerous efforts on load control and demand response programs. The present section provides an overview and a classification of the main type of programs that involve load management and demand response.

<u>*Programs targeting domestic and small commercial customers*</u>
Residential and small commercial customers have been mainly targeted by Direct Load Control (DLC) programs launched by utilities in order to reduce system peak load or to minimise their energy production costs. The operational procedure of these type of programs consists on the scheduling of curtailment signals to specific appliances such as air-conditioners, water-heaters, space heaters and swimming pool pumps. Most of these appliances provide a big amount of thermal inertia and can be switched off for short periods of time with small disturbance to the customer's comfort levels.
Participation on these programs requires the installation of a receiver on the customer's premises that allows the reception and execution of the curtailment actions. Customers participating on these programs are usually paid through a fixed reduction on the monthly bill. The fact that the communication systems do not allow the communication from the

customer side to the control centre makes difficult to check the accomplishment of the control action.
There are many US utilities offering these types of program, examples of which are: Duke Power, Virginia Electric and Power Company or Otter Tail Power Company. The number of households participating on each program can be up to several millions.

Utilities have also offered Time of Use Rates (TOU) to domestic customers. The idea is to offer electricity with different prices at different times of the day, having in mind that both the price and the times are pre-arranged and fixed. This type of program requires the installation of advanced meters that record the electricity usage over the different price & time intervals. Depending on the utility the number of price intervals range from two to four.
Some efforts have been made in order to adopt more flexible tariff structures, such as critical peak pricing or real time pricing such as the Norwegian electricity market where different price based contracts as applied to the retail power market (spot price, spot price with maximum price limit, …).

Programs targeting big commercial and industrial customers
Each of these customers use much more energy than any domestic customer and therefore are more interesting in terms of load management, this is why big commercial and industrial customers have been more heavily involved in demand response activities over the last years. Main program types are described below:

Time of Use Rates
In the same way as domestic customers, industrial customers have been offered the chance to select tariff structures with different price intervals. The possibilities range from fixed prices and time intervals, to completely variable pricing such as real time pricing where the price that the customer pays to his supplier directly reflects the price that the supplier has paid in the market. The electricity bill of a customer under this type of contract is very variable and encourages the customer to be aware of price forecasts and tailor its load consumption to them. This contract type eliminates all risk to the supplier and passes it to customers. The scheme obviously requires advanced metering that records the consumption every hour or half an hour.
Between the two previous extreme possibilities there is a wide range of possibilities:
Critical-peak-pricing: Under this type of contract the customer receives electricity at a given fixed price except on some particular days where the price is much higher. The number of critical days per year is agreed in advance but their timing is unknown. They are usually communicated one day in advance. The biggest program of this type is operated by EDF (Electricité de France) with 10 million customers.
Dynamic pricing: The price that customers pay to the supplier is linked to the wholesale price but not directly. There are different levels of agreement where customers and supplier share the risk of wholesale price volatility.

Interruptible programs
Interruptible programs have been very popular offering cheaper electricity to customers with the capability of reducing their consumption when requested by the utility or the system operator. Customers have to provide a minimum amount of load reduction, typically 1MW, and be ready to execute the reduction request at any time. Contracts establish the minimum notification margin (typically from 10 minutes to an hour), the maximum

duration of the interruption and the maximum number of interruptions per year. The communication of the load reduction request can be done by telephone, email or fax.
Load reduction has to be accomplished by the customer itself, and the failure to comply with a request involves heavy economic penalties.

The conditions to participate on interruptible programs are usually stiff and do not allow a wide participation on them. In order to facilitate the participation of more electricity users there are more flexible interruptible load programs that are usually called curtailable load programs. In these programs the minimum amount of load reduction is smaller (100 kW), the number of curtailment requests is also smaller and no compliance penalties are not so severe.

6.1.3 Hypothesis

As explained on the introduction, the demand side management system that has been developed is tailored to the particular nature of microgrids. The control is centralised on a microgrid central controller and the customers are equipped with remotely controllable devices. These control devices are a natural extension of remote metering devices with additional capabilities.
Two way communication between the microgrid central controller and these devices is also an available feature.

6.1.4 Indel project

At the beginning of the nineties the biggest Spanish utilities detected that there was a lack of knowledge about demand behaviour and about the way in which end-users consume electricity and decided to create a project to investigate it. The INDEL project was born.
Electricity demand was divided into different sectors and then these sectors were studied in detail. The project focused on the domestic and residential demand segments, carrying on a detailed description of each of them.
Real time monitoring of individual appliance consumption was carried out and questionnaires were handed out to customersin order to complete the study.
Project results included several applications and tools (forecasting, …), methodology, databases and a public available report. This report provides a group of tables and graphs with data referred to the year 1997. The interesting part for DSM development is that the project provides the diversified consumption curves of different appliances.
The way this curves are built is the following: The consumption of a statistically high enough number of devices with similar characteristics is monitored in real time by meters with recording capabilities. At each time step of a day the real time power consumption of all the monitored devices is added together and a curve is obtained for each day. If we monitor the load for a long time, during a complete year for example, we will be able to predict the behaviour of the device type being monitored depending on the season, day of the week, temperature…
Figure 6.1 shows an example of a diversified load consumption curve when 1500 washing machines were monitored is shown. The curve is normalised for one washing machine consumption and is given for a particular day.

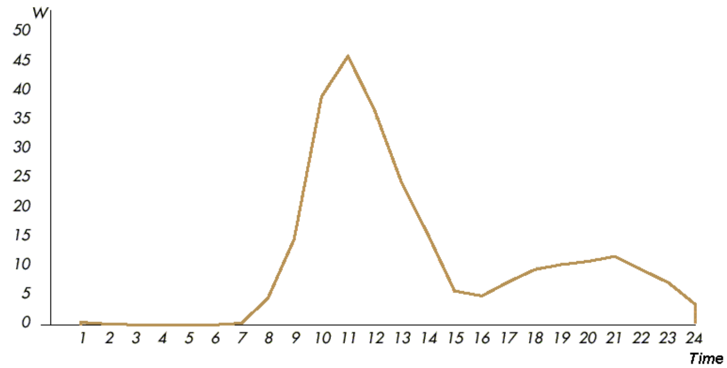

Figure 6.1 Example of a diversified load curve

This curve is telling us that 11 AM is the time when more washing machines are connected. It also tells us that nobody uses the washing machine at night.

The study is continued nowadays, some data is updated daily and made public by means of a web server. Therefore residential, commercial and industrial load profiles are available for each day at hourly time steps. Complementary studies about appliance penetration degree from other sources (this type of data was obtained through above mentioned surveys for INDEL project purposes) are used to extrapolate information.

6.2 Load shifting

6.2.1 Introduction

As stated before the demand side management system runs two different algorithms: one that calculates load curtailment actions and one that calculates load shifting actions. This chapter explores the load shifting algorithm in detail.

Labein's developed shifting algorithm targets the domestic demand segment. It is based on the fact that the consumption of some appliances can be deferred in time resulting on small disturbance to customer's comfort. Four shiftable appliance types have been identified: washing machines, dryers, dish-washers and storage water heaters. The control over these device types offers great control opportunities. Figure 6.2 presents two curves: the first one represents the total Spanish system load during a typical winter day of the year 2003 and the second one the part of that load consumed by washers, dryers and dish-washers. The data is provided by the INDEL project.

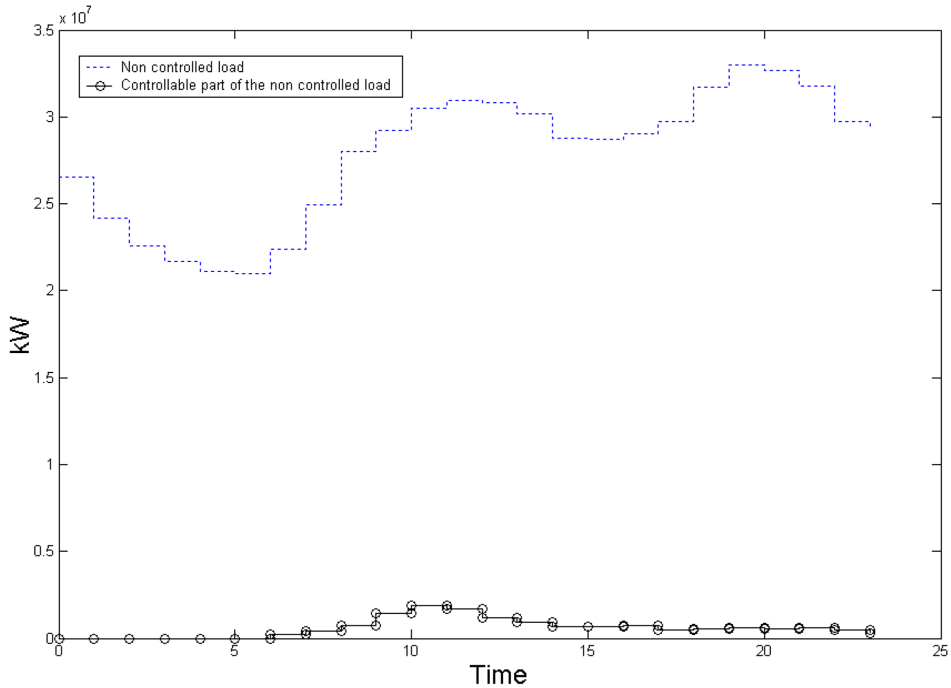

Figure 6.2 Daily system load and control margin

In this example it can be seen that if we are able to control the connection instant of those three appliance types the available improvement margin is significant, specially during the morning peak.

6.2.2 Architecture

The DSM control is centralised on the MGCC, it is an independent module within the MGCC. As stated before the function of the shifting algorithm is to delay the connection instant, that is when the consumption really happens, of several devices in order to bring the forecasted load curve as close as possible to a previously defined objective load curve.
The algorithm is run advance at the beginning of a pre-defined control period and then the actions are executed on real time. ***Figure 6.*** shows the information being exchanged between the MGCC and each appliance during the application of a control action. Basically when a customer presses the ON button of his appliance, the connection request is sent to the MGCC, and depending on the result of the shifting algorithm run in advance, the MGCC replies. The reply can be either the connection permission (no control action is executed), or the new connection time decided by the shifting algorithm. This process is explained in more detail on section 6.2.5.

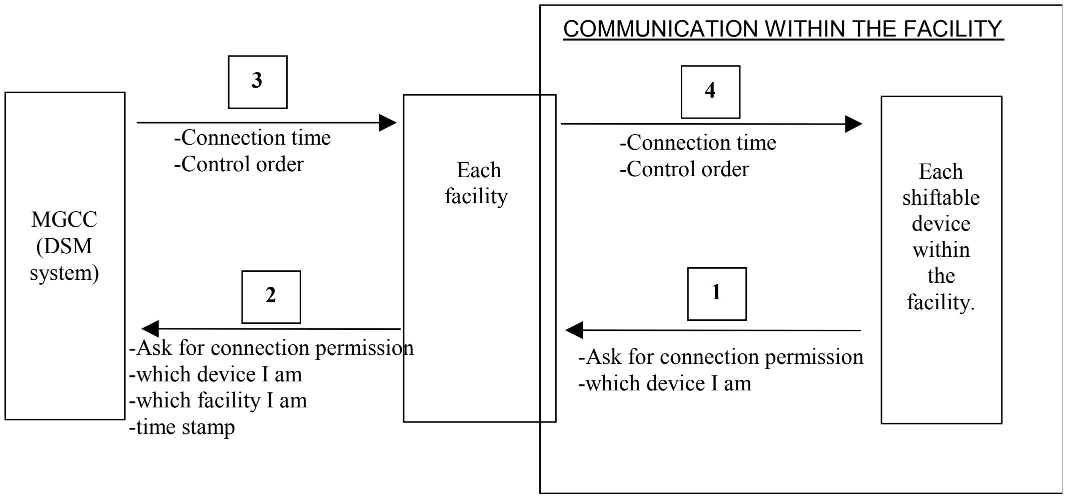

Figure 6.3 Data interchange

6.2.3 Design

The system is based on contracts signed between customers and some actor: supplier, aggregator, the microgrid or network controller, etc. Contracts are fixed and refer to each controllable device independently. The customer has the option to select from a choice of control alternatives for each device. The participant actor designs different contracts that are presented to customers.

Some possible alternatives for each controllable device type are listed below. The particular figures that are given are for example purposes only, but that type of options are considered in the developed demand side management system:

<u>Washing Machine:</u>
The customer may select one of the following five options:
1. No possible control over my washing machine.
2. My washing machine can be moved everyday to anywhere between 17 PM and 24 PM.
3. My washing machine can be moved everyday to anywhere between 8 AM and 23 PM.
4. My washing machine can be moved everyday to anywhere before 24 PM.
5. The connection of my washing machine can be delayed for a maximum of 4 hours.

Obviously the obtained bill reduction could be different according to the selected option. If option 1 is selected there is not any bill reduction.
In this example the central controller has decided to offer 3 time gaps: 17PM-24PM, 8AM-23PM and anytime before 24PM. It has also offered the possibility to allow a maximum connection delay.

For dryers and dish-washers similar type of contracts are stabilised.

<u>Water Heater</u>
The water heater electricity consumption is controlled in the form of shifting. In this case the contracts are different from the previous shiftable devices. The hot water storage

capacity is limited and in order to minimise the possibility of the customer running out of hot water, a maximum allowable delay is specified.
The maximum delay from the moment that the amount of water stored in the tank drops below the 30% is set to 4 hours. A set of possible contract options is presented below:

1. No possible control over my water heater
2. My water heater consumption can be delayed for a maximum of 1 hour.
3. My water heater consumption can be delayed for a maximum of 2 hours.
4. My water heater consumption can be delayed for a maximum of 4 hours.

The options selected by all the customers for each individual device are stored in a database that is easily accessed by the DSM system.
The DSM system calculates control actions that fulfil the signed contracts. In the case of an emergency situation that requires an out of contract load control action, the microgrid central controller itself (not the DSM system) would assume responsibility and possibly pay penalties.

The system parameters are the definition of the control period as well as the length of the considered time steps. This information is passed to the DSM system by the MGCC. For example the MGCC could decide that the control period is 24 hours long from 00:00AM to 24:00PM and that the length of the considered time steps is 30 minutes.

Data describing customer contracts is required. The shifting algorithm requires:
- Number of customers and id.
- For each customer:
  - Customer type: domestic or commercial.
  - Existing shiftable devices and id.
  - Which of the contract options have been selected for each shiftable device.
  - Load consumption pattern of each device.

The pattern is a curve that represents the load consumption curve of the device at each time step of the duration of its consumption cycle. ***Figure*** shows and example of the load consumption pattern of a washing machine when the time step length is 30 minutes.

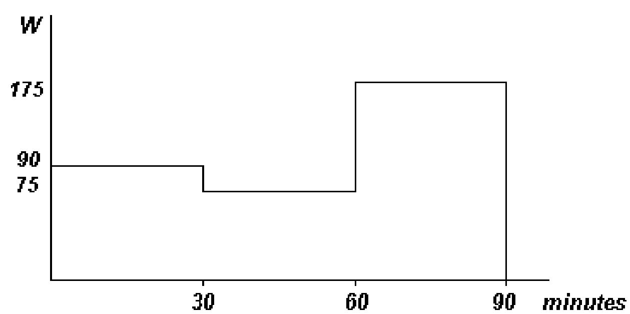

Figure 6.4 Example of a load consumption pattern

This customer related information is stored in a database that can be accessed by both the MGCC and the DSM system. For the correct operation of the shifting algorithm loads showing the same consumption pattern and under the same contract option are grouped together.

Apart from the contract information the shifting algorithm requires other inputs from different modules of the MGCC that are explained below:

- MGCC provides a forecasted load consumption value for each of the time steps of the control period. This curve is called forecasted load curve. It represents the load that it is expected to be consumed if no control actions are applied. Load forecasting algorithms used by the MGCC are not relevant to the DSM system.
- MGCC gives an objective load value for each of the time steps of the considered control period. These values form the so-called objective load curve. The calculation of it may be a complex procedure that depends on many variables and on the weight that we want to give to each of them. Several possible alternatives are given on the introduction such as maximise renewable sources, minimise power exchanges with the mains, energy market costs, etc.. The calculation of this curve is out of the scope of the DSM system, it is just an input.

If the microgrid is considered as a whole, then only one objective load curve and one forecasted load curve will be passed to the shifting system. The DSM system does not have into consideration factors such as losses or voltage drops when it calculates the control actions, nor it cares about how to distribute the control actions between loads regarding their topological situation.
If the microgrid size is high, the control actions could seriously unbalance the loading situation causing increases in losses, voltage drops or line overloading; the MGCC will need to separate the microgrid into parts and provide different objective and forecasted load curves for each part of the network and then execute DSM system each of part of the network.

The shifting algorithm needs an estimation of the number of devices of each group (same contract and same consumption pattern) that is expected to be connected at each time step of the control period.
In order to obtain accurate results the diversified consumption curves have to be built with as many customers as possible. If the number of controlled customers is small the diversity of the curves may not be enough and the shifting system as described on this document could be useless.
It is normally assumed that remote metering devices are the first step before installation of intelligent distributed devices into customer premises. In any case, diversified load consumption curves can be obtained by disaggregation procedures applied on real data for DSM economic impact evaluation studies

The following table summarises the general inputs required by the load shifting algorithm:

ORIGIN	INFORMATION	
MGCC	Control period	
	Length of the time steps	
	Objective load curve	
	Forecasted load curve	
	Diversified load consumption curve of each device type	
Customer and contracts	Number of customers	
	For each	Customer type

ORIGIN	INFORMATION	
databases	*customer*	Existing shiftable devices
		Selected contracted option for each shiftable device
		Load consumption pattern for each shiftable device type

Table 6.1 *Inputs to the shifting algorithm*

In order to adapt the contract options to a format suitable for the shifting algorithm, a pre-process is applied. At the beginning of this section some different possible contract options that a customer receives are presented. For shiftable appliances two different contract types can be found:

- A time gap where the appliances can be moved to.
- A maximum allowable connection delay.

The optimisation algorithm requires two values for each shiftable appliance type and expected connection time step:

1. First possible time step where the appliance can be moved to. (s).
2. How many successive time steps (starting from s) are also possible connection times. (w).

These two values are established for every appliance and contract type for each time step. The calculation of this parameters also depends on the duration of the appliance consumption.

6.2.4 Optimisation algorithm

On this section the core of the shifting process is explained and the algorithm mathematically formulated.
The general aim of the algorithm is to schedule the connection moment of each shiftable device within the microgrid in a way that brings the total load consumption curve as close as possible to a given objective load consumption curve.
Elements and variables
Let us define the elements and variables that are used on the optimisation procedure:

General information

n — Number of time steps on the given control period.

$forecasted_i$ — Expected load consumption at time step i if no control action is applied. i=1,2,…,n

$objective_i$ — Objective load consumption at time step i. i=1,2,…,n.

Appliance groups

All the shiftable devices are grouped according to their load consumption pattern and the selected control possibility. Each group of appliances is identified with a number ranging from 1 to the number of groups.

k — Appliance group identifier.

Load consumption pattern of the devices of each group

d_k — Duration (in number of time steps) of the consumption pattern of devices in group k.

p_{ik} for i=1,2,.. , d_k Device consumption at each time step.

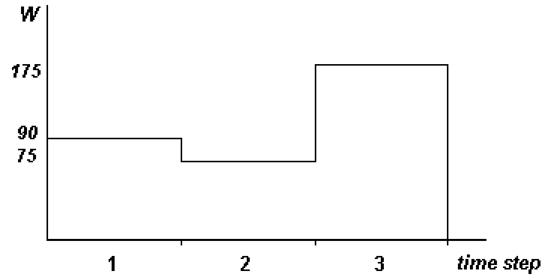

Figure 6.5 *Example of a load consumption pattern*

For the pattern of the figure d_k=3 and

p_{1k}=90 W p_{2k}=75 W p_{3k}=175 W

Expected device connections

From the dissagregation of the diversified curves the number of devices from each group that are expected to be connected at each time step of the given control period is obtained.

con_{ik} Expected number of devices of type k connecting at time step i.

There is a value for all the combinations of device types and time steps.
k =1,2,…,number of device groups.
i =1,2…,n.

Control possibilities

For each device group and based on the contracts database the following values are calculated:

s_{ik} First possible time step where the appliances of group k connecting at time step i can be moved to.

w_{ik} How many successive time steps (starting from s_{ik}) are also possible connection times for appliances of type k connecting at time step i.

There is a value of s and w for all the combinations of device types and time steps.
k =1,2,…,number of device groups.
i =1,2…,n.

Problem variables

The variables that the optimisation algorithm calculates are the following:

X_{kij} Number of type k devices that were originally expected to be connected at time step i and that after the optimisation are going to be connected at time step j.

X_{kii} Number of type k devices that were originally expected to be connected at time step i and that after the optimisation are still connected at time step i .

Problem formulation

The optimisation problem is mathematically formulated using a linearly constrained quadratic program.

As stated before the aim of the algorithm is to bring the total load consumption curve as close as possible to the given objective load curve. The function to minimise can then be represented as the sum of the squares of the difference between the load and the objective curves at each time step:

$$\sum_{z=1}^{n}\left(load_z - objective_z\right)^2 \qquad (6.2.1)$$

The values for the objective function at each time step are given and fixed. The load at each time step is a function of many elements.

Load at time step z:

$$load_z = forecasted_z + connected_z - disconnected_z \qquad (6.2.2)$$

where:

$connected_z$ is the amount of load that is connected due to control actions at time step z and is the load

$disconnected_z$ that is disconnected due to control actions at time step z.

The term $connected_z$ can be separated into two parts:

- The increase in the load at time step z due to new device connections scheduled for time step z.
- The increase in the load at time step z due to new device connections scheduled for the time steps that precede z.

$$connected_z = \sum_{\substack{i=1 \\ i\neq z}}^{n}\sum_{k=1}^{n1} X_{kiz}\cdot p_{1k} + \sum_{l=1}^{n2}\sum_{\substack{i=1 \\ i\neq z-l}}^{n}\sum_{k=1}^{n3} X_{ki(z-l)}\cdot p_{(l+1)k} \qquad (6.2.3)$$

where:

n	Total number of time steps
n1	Total number of device groups
n2	The biggest d_k of all the device groups
n3	Number of device groups where d_k >= (l+1)

The term $disconnected_z$ can be separated into two parts:

- The decrease in the load at time step z due to the delay in connection of devices that were originally expected to start their consumption at time step z.
- The decrease in the load at time step z due to the delay of devices that were originally expected to start their consumption at the time steps that precede z.

$$disconnected_z = \sum_{\substack{j=1 \\ j\neq z}}^{n}\sum_{k=1}^{n1} X_{kzj}\cdot p_{1k} + \sum_{l=1}^{n2}\sum_{\substack{j=1 \\ j\neq z-l}}^{n}\sum_{k=1}^{n3} X_{k(z-l)j}\cdot p_{(l+1)k} \qquad (6.2.4)$$

where n, n1, n2 and n3 are the same as before.

Substituting Eq. 6.2.3 and 6.2.4 on 6.2.2, we get:

$$load_z = forecasted_z + \left(\sum_{\substack{i=1\\i\neq z}}^{n} \sum_{k=1}^{n1} X_{kiz} \cdot p_{1k} + \sum_{l=1}^{n2} \sum_{\substack{i=1\\i\neq z-l}}^{n} \sum_{k=1}^{n3} X_{ki(z-l)} \cdot p_{(l+1)k} \right) - \left(\sum_{\substack{j=1\\j\neq z}}^{n} \sum_{k=1}^{n1} X_{kzj} \cdot p_{1k} + \sum_{l=1}^{n2} \sum_{\substack{j=1\\j\neq z-l}}^{n} \sum_{k=1}^{n3} X_{k(z-l)j} \cdot p_{(l+1)k} \right)$$

and substituting this last equation on Eq. 6.2.1:

$$\sum_{z=1}^{n} \left(forecasted_z + \left(\sum_{\substack{i=1\\i\neq z}}^{n} \sum_{k=1}^{n1} X_{kiz} \cdot p_{1k} + \sum_{l=1}^{n2} \sum_{\substack{i=1\\i\neq z-l}}^{n} \sum_{k=1}^{n3} X_{ki(z-l)} \cdot p_{(l+1)k} \right) - \left(\sum_{\substack{j=1\\j\neq z}}^{n} \sum_{k=1}^{n1} X_{kzj} \cdot p_{1k} + \sum_{l=1}^{n2} \sum_{\substack{j=1\\j\neq z-l}}^{n} \sum_{k=1}^{n3} X_{k(z-l)j} \cdot p_{(l+1)k} \right) - objective_z \right)^2$$

This is the function that the optimisation algorithm minimises.

In a general formulation of the problem the number of variables would be:

Number of variables= $n \cdot n \cdot n1$

The particularities of the shifting procedure reduce significantly this number of variables:

- The device connections can only be delayed and therefore:

  $\forall j < i \qquad X_{kij} = 0$

- The contract options limit further the number of variables:
  For each device group k and time step i:

  $\forall j < s_{ki} \qquad X_{kij} = 0$

  $\forall j > (s_{ki} + w_{ki}) \qquad X_{kij} = 0$

That is, the number of type k devices which consumption is delayed from time i to time j always satisfy signed contracts: maximum delay ($s+w$) and gap length (w)

Constraints

Once that the function to minimise and the variables are defined, constraints are established. There are two constraint types:

1. The number of devices that we move cannot be negative:

   $\forall i, j, k \quad X_{kij} \geq 0$

2. The expected number of controllable type k devices connecting at time step i must be equal to the number of devices that are not moved plus the devices that are moved:
   For each device group k and time step i:

$$con_{ik} = \sum_{j=1}^{n} X_{kij}$$

In summary the formulation of the problem is: **Find the values of the variables X that minimise the function**:

$$\sum_{z=1}^{n} \left(forecasted_z + \left(\sum_{\substack{i=1\\i\neq z}}^{n} \sum_{k=1}^{n1} X_{kiz} \cdot p_{1k} + \sum_{l=1}^{n2} \sum_{\substack{i=1\\i\neq z-l}}^{n} \sum_{k=1}^{n3} X_{ki(z-l)} \cdot p_{(l+1)k} \right) - \left(\sum_{\substack{j=1\\j\neq z}}^{n} \sum_{k=1}^{n1} X_{kzj} \cdot p_{1k} + \sum_{l=1}^{n2} \sum_{\substack{j=1\\j\neq z-l}}^{n} \sum_{k=1}^{n3} X_{k(z-l)j} \cdot p_{(l+1)k} \right) - objective_z \right)^2$$

$\forall j < i \qquad X_{kij} = 0$

For each device group k and time step i:

$\forall j < s_{ki} \quad X_{kij} = 0$

$\forall j > (s_{ki} + w_{ki}) \quad X_{kij} = 0$

subject to the following constraints:

$\forall i, j, k \quad X_{kij} \geq 0$

For each device group k and time step i:

$$con_{ik} = \sum_{j=1}^{n} X_{kij} \tag{6.2.5}$$

This optimisation problem is a linearly constrained quadratic program. To solve it a code developed by Y. Ye that uses the interior ellipsoidal trust region and barrier function algorithm with dual solution updating technique is employed.

In a problem with this formulation obtained values of X are real numbers and we need integer numbers (fractions of devices cannot be moved). This implies that the result has to be rounded. Different criteria can be used to decide the rounding procedure, a possible conservative criterion could be:

For each device group k and time step i: All the calculated X_{kij} are truncated to the closest integer towards zero and the resulting X_{kii} is calculated using equation 6.2.5:

$$con_{ik} = X_{kii} + \sum_{\substack{j=1 \\ i \neq j}}^{n} X_{kij}$$

$$X_{kii} = con_{ik} - \sum_{\substack{j=1 \\ i \neq j}}^{n} X_{kij}$$

The procedure is conservative in the sense that the number of shifting actions is decreased.

6.2.5 Real time application of the actions

The shifting algorithm is run in advance, before the start of the given control period. When the algorithm finishes, a solution is found and a list containing the shifting actions is obtained. The list provides for each time step of the control period a set of values:

How many appliances of each type that are expected to be connected at that time step, have to be connected at each of the next time steps.

The actions have to be executed in real time during the control period making use of the two way communication capabilities of the system. The block diagram on *Figure 6.* shows the process followed starting from the instant when a customer presses the ON button on a shiftable appliance.

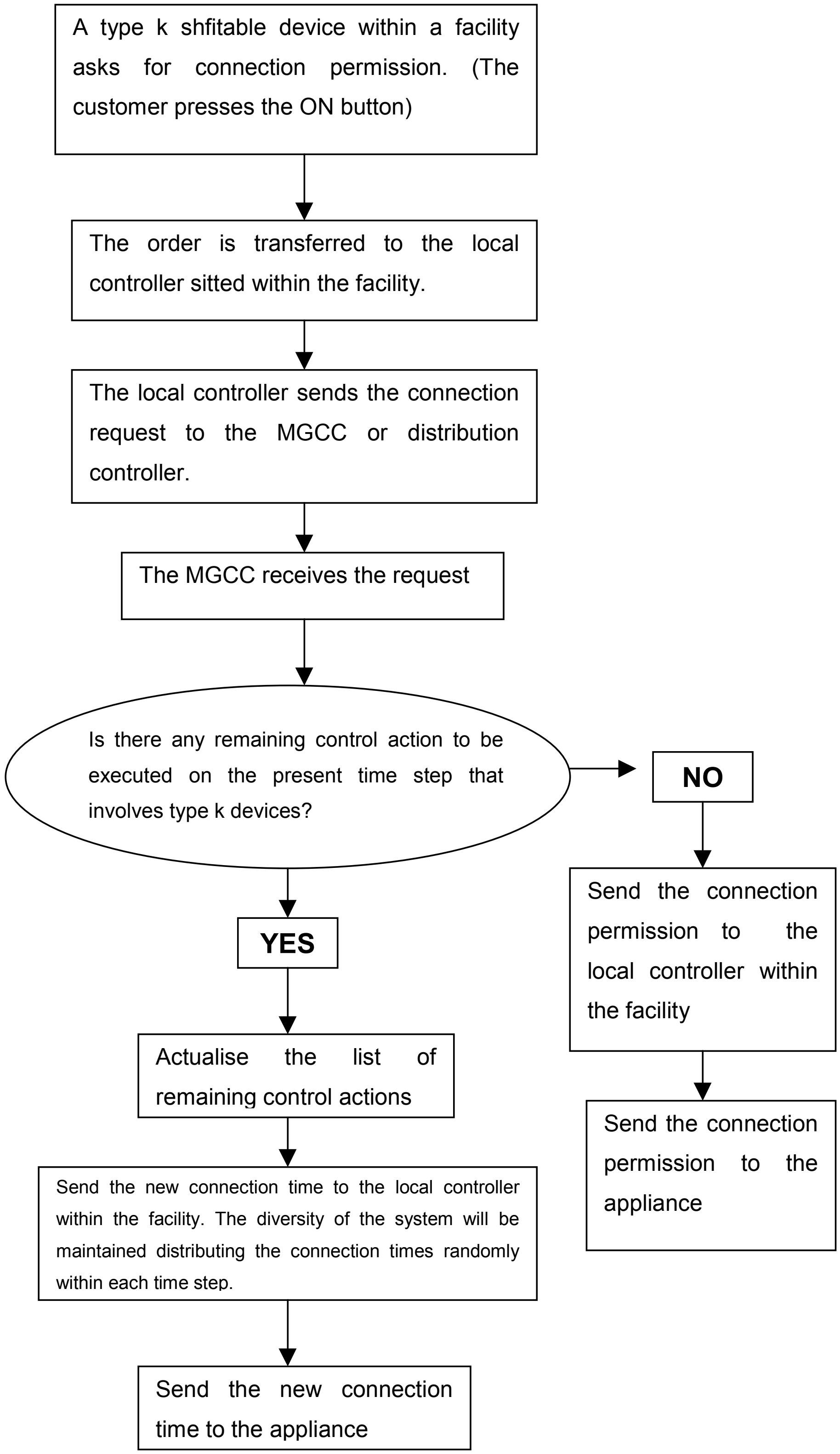

Figure 6.6 *Application of the actions*

The duration of the cycle (time between the moment of button pressing and the connection moment) for an appliance that is not controlled varies depending on the existing communication infrastructure.

An important issue of the real time application of the scheduled control actions is the possible mismatch between the expected number of device connections at a time step and the actual number of devices that finally send the connection request. Two cases can arise:

1. There are less connection requests than the expected number of controllable device connection requests. This is the most onerous case, the shifting algorithm has decided to move some appliances that finally are not connected at their expected time. The way to act is to add the non-executed control actions to the action list of the next time step, hoping that there will be an excess of connection requests.
2. There are more connection requests than the expected number of controllable device connection requests. If there is an excess of control actions from previous time steps they will be executed. If there are still more connection requests, the MGCC allows the free connection of these devices.

In order to avoid the first case, when the diversified curves are dissagregated some security coefficients that tend to reduce the expected number of device connections are introduced, even if we know that this reduction limits the possible improvement margin offered by the DSM system.

6.2.6 Case studies

The shifting algorithm presented on this document has been successfully implemented in Matlab and is fully operative. On the Deliverable DC2 different case studies analysing system performance and suitability of control actions.

6.3 Load Curtailment

6.3.1 Introduction

The curtailment algorithm is different and independent from the shifting algorithm. Curtailment control actions are not desired because they produce clear inconveniences to customers and therefore the algorithm is intended to be run just occasionally in cases of possible system contingency.

The targeted devices by the curtailment algorithm are both domestic and commercial air conditioning units and electric central heating units. The idea is to make use of the thermal inertia offered by these devices and reduce their load consumption maintaining acceptable comfort levels. It is be assumed that the controllable devices have the capability to reduce their consumption a given amount of their nominal value by themselves acting over their duty cycle.

6.3.2 Architecture

The overall working procedure is similar to the shifting algorithm: The system controller (the MGCC for a microgrid) establishes a control period and an objective load curve for it. Based on the contracted control possibilities and on an estimation of the number of device connections at each time step, the curtailment algorithm decides the control actions that bring the load consumption as close as possible to the given objective load curve. The control periods are shorter than in the shifting algorithm, typically from 1 to 2 hours, and are embedded on the shifting control period.

The application of the control actions is different to those on the shifting process. Here when a customer connects his air-conditioner, it start its consumption without waiting for any order from the MGCC. It sends the connection signal for information purposes. When a contingency situation occurs, the curtailment algorithm is run and if it calculates that a particular air-conditioner has to be controlled it sends the consumption reduction order to such appliance. ***Figure 6.*** shows the information interchange between an air-conditioner and the MGCC.

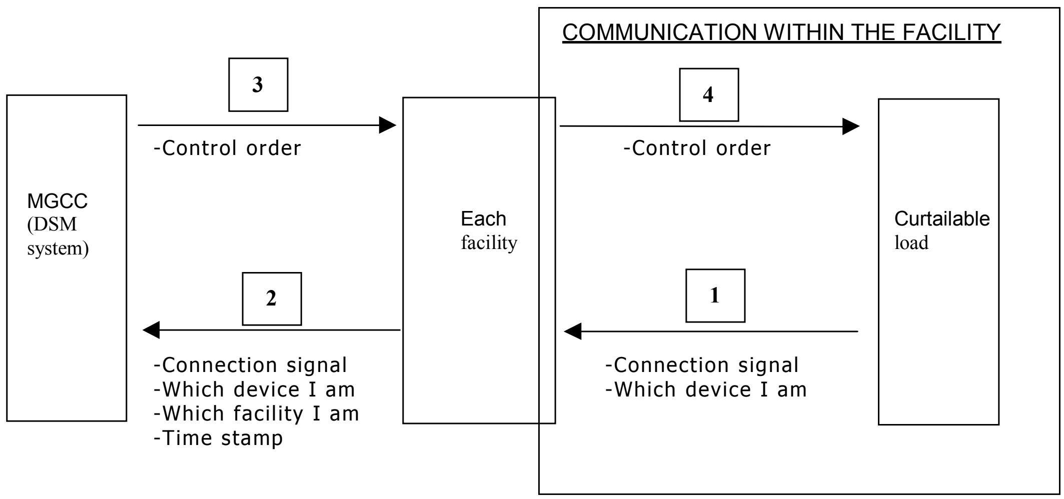

Figure 6.7 Data interchange

6.3.3 Design

In the same way as the shifting algorithm the control possibilities allowed by each customer are established by contracts. An example of some possible options for a curtailable device are the following: The customer decides from the following options:

1. No possible control over my air conditioner.
2. The cycle of my AC can be changed during a maximum of 3 consecutive hours per day in order to reduce a 30% its power consumption during those 3 hours.
3. The cycle of my AC can be changed during a maximum of 4 consecutive hours per day in order to reduce a 50% its power consumption during those 4 hours.

Each of these options comes with a study that provides an idea of the temperature variations that will occur for different outside temperatures and air conditioning devices to show practical effects and allow a reasoned answer from customers.

The following table summarises the inputs required by the algorithm:

ORIGIN	INFORMATION	
MGCC	Curtailment control period	
	Length of the time steps	
	Objective load curve	
	Forecasted load curve	
	Diversified load consumption curve of each AC or heating device type	
Customer and contracts	Number of customers	
	For each customer	Customer type

ORIGIN	INFORMATION	
databases		Existing AC or heating devices
		Selected contracted option for each device
		Load consumption pattern for each device

Table 6.2 *Inputs to the curtailment algorithm*

In the same way as the shifting algorithm, the curtailment algorithm requires an estimation of the number of devices of each type connecting at each time step of the given control period.
The behaviour of air conditioning and heating loads is different from the behaviour of shiftable devices. Shiftable devices have a particular fixed load consumption pattern. A drying cycle for example will always be exactly the same, it will last for a fixed amount of time and follow a fixed consumption curve. A thermostat controlled air conditioner has not got a fixed pattern. From the moment that it is switched ON to the moment that it is switched OFF it can follow different consumption curves depending on the weather conditions and on the device temperature settings. The length of the ON period is also variable.
In order to model the behaviour of the curtailable devices in an appropriate way two different curtailable device types are considered:

Type1: Devices that behave similarly to shiftable devices: the shape and length of their consumption pattern is very similar every time that they are used and therefore it can be considered constant. This is the case of small air conditioning and space heating units that are turned ON for not very long periods of time on days of adverse weather conditions.
They are modeled and processed in exactly the same way as a shiftable device. After the process the expected number of device connections at each time step is obtained.

Type2: Devices that are ON for long periods of time. Typical examples of this type of device are commercial air conditioning and space heating units that are usually ON all the time that the shops are opened to the public. Devices installed on office buildings also behave in a similar manner. Some domestic devices that climatise big spaces are also ON for long periods of time.
Devices of this type have to be modelled in a different way. It will be assumed that the devices are ON the complete day, their load consumption pattern is considered to be exactly the same as the diversified curve normalised for one device. There is not need for any dissagregation, all the devices start their consumption at the first time step of the day and all of them finish at the last time step of the day.

6.3.4 Optimisation algorithm

The aim of the curtailment algorithm is to calculate the control actions that bring the load consumption during the given curtailment interval as close as possible to an objective load consumption.
The differences between type1 and type2 devices make necessary the development of two different types of control procedures. Despite of being controlled in a different way, control actions over both type1 and type2 devices are calculated at the same time on the optimisation process.
The payback is defined as the amount of energy that has not been consumed due to the control action and that is going to be consumed as soon as the control action is finished. In most of the existing literature on load curtailment great importance is given to the payback

modelling. Payback modelling is a complicated task that requires the execution of multiple field tests.
The curtailment algorithm presented on this document does not consider payback. The reason for this is that the control actions that are calculated on this algorithm do not curtail completely the consumption of the devices, they act over the duty cycle of the devices reducing their consumption on a given percentage. The smallest the reduction, the smallest the payback. It will be assumed that the payback effect due to control actions that do not completely curtail the device consumption is zero.
In the following the curtailment optimisation is presented:

Elements and variables
Let us define the elements and variables that are used on the optimisation procedure:

General information

n	Number of time steps on the shifting control period where the curtailment control period is embedded
n_{curta}	Number of time steps on the given curtailment control period
z_f	Position of the first time step of the curtailment control period on the shifting control period
z_l	Position of the last time step of the curtailment control period on the shifting control period
$forecasted_i$	Expected load consumption at time step i if no control action is applied. i=$z_f,\ldots,z_l$
$objective_i$	Objective load consumption at time step i. i=$z_f,\ldots,z_l$

Appliance groups
Devices are grouped according to their load consumption pattern and selected control possibility in the same way as the shiftable devices. There are groups of type1 devices and groups of type2 devices.
Each appliance group will be identified with a number ranging from 1 to the number of groups.

k	Appliance group identifier

Load consumption pattern of the devices of each group

For Type1 devices

d_k	Duration (number of time steps) of the consumption pattern of the devices in group k.
p_{ik}	Device consumption at each time step. for i=1,2,.. , d_k

For Type2 devices
The discreet diversified load consumption curve for each device group normalised for one customer are used.

$d_k = n$	Duration of the shifting control period.
p_{ik}	Value of the curve at each time step. for i=1,2,.. ,n

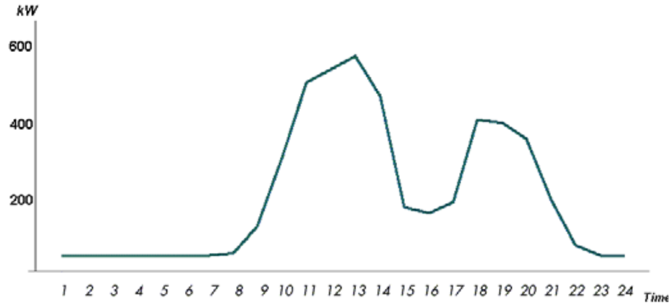

Figure 6.8 *Example of the diversified curve of an air conditioner*

Expected device connections

For Type1 devices

From the dissagregation of the diversified curves the number of devices from each group that are expected to be connected at each time step of the given control period is obtained.

con_{ik}	Expected number of devices of type k connecting at time step i.

There is a value for all the combinations of device types and time steps.
k=1,2,…,number of device groups.
i=1,2…,n.

For Type2 devices

All the devices are considered to be continuously connected during the control period.

con_k	Expected number of devices of type k that are connected during the control period.

Control possibilities

For each device group and based on the contracts database two values are established:

C_k	Maximum possible duration of the control action over devices of group k.
r_k	Allowable consumption reduction during the control action over devices of group k (In per-unit)

Problem variables

The variables that the optimisation algorithm calculates are the following:

For Type1 devices

X_{khi}	Number of type k devices that are expected to be connected at time step i and that are going to be controlled during h time steps. If i is before the start of the curtailment control period the devices will start to be controlled at the first time step of the curtailment period. The control action consists in reducing the device consumption on r_k.
X_{k0i}	Number of type k devices that are expected to be connected at time step i and that after the optimisation are not going to be controlled.

For Type2 devices

Y_{khi}	Number of type k devices that start to be controlled at time step i and are controlled during h time steps. The time step i is within the curtailment control period. The control action consists in reducing the device

consumption on r_k.

Y_{k0} Number of type k devices that are not controlled.

Problem formulation

In the same way as the shifting algorithm the optimisation problem will be mathematically formulated using a linearly constrained quadratic program. The function to minimise can be represented as the sum of the squares of the difference between the non controlled load and the objective curves at each time step of the curtailment control period:

$$\sum_{z=z_f}^{z_l} \left(load_z - objective_z\right)^2 \tag{6.3.1}$$

The values for the objective function at each time step are given and fixed. The load at each time step is a function of many elements.

Load at time step z:

$$load_z = forecasted_z - disconnected_z \tag{6.3.2}$$

where $disconnected_z$ is the load that is eliminated from time step z.

The term $disconnected_z$ can be separated into two parts:

$$disconnected_z = disconnected\_t1_z + disconnected\_t2_z \tag{6.3.3}$$

where:

- $disconnected\_t1_z$: Load eliminated at time step z due to control actions over type1 devices.
- $disconnected\_t2_z$: Load eliminated at time step z due to control actions over type2 devices.

The calculation of each term will be explained separately:

Load eliminated at time step z due to control actions over type1 devices ($disconnected\_t1_z$)

Let us first limit the number of variables X_{khi}:

i is defined when:

$i > z_f - d_k$ for each combination of k and i

$i \le z_l$ for each i

For each combination of k and i two values are defined:

$if1_{ki}$ The smallest i that fulfils the above conditions

$il1_{ki}$ The biggest i that fulfils the above conditions

h is defined when:

$h \ge 1$ for each k

$h \le C_k$ for each k

$$g = i - z_f + 1 \tag{6.3.4}$$

if $g > 0$ $h \le n_{curta} - g + 1$ for each i or (we take the most restrictive)

$h \le d_k$

if $g \le 0$ $h \le n_{curta}$ for each i

or (we take the most restrictive)

$h \le g + d_k - 1$ for each i

For each combination of k and i two values are defined:

$hf1_{ki}$ The smallest h that fulfils the above conditions

$hl1_{ki}$ The biggest h that fulfils the above conditions

In summary, for each combination of k and i X_{khi} exists when:

$$if1_{ki} \le i \le il1_{ki} \quad \text{and} \quad hf1_{ki} \le h \le hl1_{ki}$$

The term $disconnected\_t1_z$ can be separated into two parts:

- The decrease in the load at time step z due to the control over type1 devices that are expected to start their consumption at time step z.
- The decrease in the load at time step z due to the control over type1 devices that are originally expected to start their consumption at the time steps that precede z.

$$disconnected\_t1_z = \sum_{k=1}^{n1} \sum_{h=1}^{hl1_{kz}} X_{khz} \cdot p_{1k} \cdot r_k + \sum_{l=1}^{n2} \sum_{k=k_1}^{k_2} \sum_{h=h_1}^{h_2} X_{kh(z-l)} \cdot p_{(l+1)k} \cdot r_k \tag{6.3.5}$$

where:

n1	Total number of type1 device groups
n2	The biggest d_k of all the type1 device groups
k_1	First type 1 device group that fulfils: $d_k \ge l+1$
k_2	Last type 1 device group that fulfils: $d_k \ge l+1$
h_1	Smallest duration that exists and fulfils: if $(z-l) < z_f$ $h \ge g$ where $g = z - z_f + 1$ if $(z-l) \ge z_f$ $h \ge l+1$
h_2	Longest duration that exists and fulfils: if $(z-l) < z_f$ $h \ge g$ where $g = z - z_f + 1$ if $(z-l) \ge z_f$ $h \ge l+1$

<u>Constraints for type1 devices:</u>

1. The number of devices that we control cannot be negative:

   $\forall k, h, i \qquad X_{khi} \ge 0$

2. The expected number of controllable type k devices connecting at time step i must be equal to the number of devices that are not controlled plus the devices that are controlled:

   For each type1 device group k and time step i:

$$con_{ik} = X_{k0i} + \sum_{h=1}^{hl1_{ki}} X_{khi}$$

Load eliminated at time step z due to control actions over type2 devices ($disconnected\_t2_z$)

Let us first limit the number of variables Y_{khi}:

i is defined when:

$i \geq z_f$ for each i

$i \leq z_l$ for each i

h is defined when:

$h \geq 1$ for each k

$h \leq C_k$ for each k

$h \leq n_{curta} - g + 1$ for each i. Where $g = i - z_f + 1$

For each combination of k and i two values are defined:

$hf2_{ki}$ The smallest h that fulfils the above conditions

$hl2_{ki}$ The biggest h that fulfils the above conditions

In summary, for each combination of k and i Y_{khi} exists when:

$z_f \leq i \leq z_l$ and $hf2_{ki} \leq h \leq hl2_{ki}$

The term $disconnected\_t2_z$ can be separated into two parts:

- The decrease in the load at time step z due to the control over type2 devices that start to be controlled at time step z.
- The decrease in the load at time step z due to the control over type2 devices that start to be controlled at the time steps that precede z.

$$disconnected\_t2_z = \sum_{k=1}^{n5} \sum_{h=1}^{hl2_{kz}} Y_{khz} \cdot p_{zk} \cdot r_k + \sum_{l=1}^{n6} \sum_{k=1}^{n5} \sum_{h=h_3}^{h_4} Y_{kh(z-l)} \cdot p_{zk} \cdot r_k \quad (6.3.6)$$

where:

n5	Total number of type2 device groups
n6	Minimum between (g-1) and the biggest (h-1) of all type2 device groups. Where $g = z - z_f + 1$
h_3	Smallest duration that exists and fulfils: $h \geq l+1$
h_4	Longest duration that exists and fulfils: $h \geq l+1$

Constraints for type2 devices:

1. The number of devices that we control cannot be negative:

   $\forall k, h, i \qquad Y_{khi} \geq 0$

2. The expected number of controllable type k devices must be equal to the number of type k devices that are not controlled plus the devices that are controlled:

   For each type2 device group k:

$$con_k = Y_{k0} + \sum_{i=z_f}^{z_l} \sum_{h=1}^{hl2_{ki}} Y_{khi}$$

Substituting equations 6.3.5 and 6.3.6 on equation 6.3.3:

$$disconnected_z = \left(\sum_{k=1}^{n1} \sum_{h=1}^{hl1_{kz}} X_{khz} \cdot p_{1k} \cdot r_k + \sum_{l=1}^{n2} \sum_{k=k_1}^{k_2} \sum_{h=h_1}^{h_2} X_{kh(z-l)} \cdot p_{(l+1)k} \cdot r_k \right) + \left(\sum_{k=1}^{n5} \sum_{h=1}^{hl2_{kz}} Y_{khz} \cdot p_{zk} \cdot r_k + \sum_{l=1}^{n6} \sum_{k=1}^{n5} \sum_{h=h_3}^{h_4} Y_{kh(z-l)} \cdot p_{zk} \cdot r_k \right)$$

Substituting this expression on equation 6.3.2 and equation 6.3.2 on equation 6.3.1 the expression to minimise is obtained:

$$\sum_{z=z_f}^{z_l} \left(forecasted_z - \left(\left(\sum_{k=1}^{n1} \sum_{h=1}^{hl1_{kz}} X_{khz} \cdot p_{1k} \cdot r_k + \sum_{l=1}^{n2} \sum_{k=k_1}^{k_2} \sum_{h=h_1}^{h_2} X_{kh(z-l)} \cdot p_{(l+1)k} \cdot r_k \right) + \left(\sum_{k=1}^{n5} \sum_{h=1}^{hl2_{kz}} Y_{khz} \cdot p_{zk} \cdot r_k + \sum_{l=1}^{n6} \sum_{k=1}^{n5} \sum_{h=h_3}^{h_4} Y_{kh(z-l)} \cdot p_{zk} \cdot r_k \right) \right) - objective_z \right)^2$$

In summary the mathematical formulation of the curtailment problem is: **Find the values of the variables X and Y that minimise the function**:

$$\sum_{z=z_f}^{z_l} \left(forecasted_z - \left(\left(\sum_{k=1}^{n1} \sum_{h=1}^{hl1_{kz}} X_{khz} \cdot p_{1k} \cdot r_k + \sum_{l=1}^{n2} \sum_{k=k_1}^{k_2} \sum_{h=h_1}^{h_2} X_{kh(z-l)} \cdot p_{(l+1)k} \cdot r_k \right) + \left(\sum_{k=1}^{n5} \sum_{h=1}^{hl2_{kz}} Y_{khz} \cdot p_{zk} \cdot r_k + \sum_{l=1}^{n6} \sum_{k=1}^{n5} \sum_{h=h_3}^{h_4} Y_{kh(z-l)} \cdot p_{zk} \cdot r_k \right) \right) - objective_z \right)^2$$

subject to the following constraints:

$\forall k, h, i \qquad X_{khi} \geq 0$

$\forall k, h, i \qquad Y_{khi} \geq 0$

For each type1 device group k and time step i:

$$con_{ik} = X_{k0i} + \sum_{h=1}^{hl1_{ki}} X_{khi}$$

For each type2 device group k:

$$con_k = Y_{k0} + \sum_{i=z_f}^{z_l} \sum_{h=1}^{hl2_{ki}} Y_{khi}$$

The problem is a linearly constrained quadratic program that is solved with the same code used by the shifting algorithm.

In the same way as the shifting algorithm, the solution to this optimisation problem are real numbers that are transformed into integer numbers. The adopted conversion method is the one explained on Section 6.2.4.2.

<u>Possible improvements</u>

In the presented curtailment algorithm there are two aspects that offer improvement margin and that can be added to future versions of the algorithm:

- In the presented version the value of the applied reduction to devices of each type (r_k) is fixed to the maximum allowed by contract. These values could be incorporated as variables and calculated within the optimisation algorithm.
- Payback of the controlled devices could be considered to be non zero and it could be modelled and incorporated into the algorithm. In this way control actions that completely curtail the device consumption could be considered with a much bigger accuracy.

6.3.5 Real time application of the actions

The curtailment algorithm is run as soon as the MGCC or the DMS requests it. This request will usually come one or two hours before the start of the curtailment control period and the curtailment algorithm has to complete the calculation during that time gap. The calculated actions are then applied in real time during the curtailment control period.

In the same way as the shifting algorithm, for each half an hour of the curtailment control period a list of control actions is generated for both type1 and type2 devices and they are executed according to the device connection requests received by the MGCC.

The control action itself is a signal that tells the device to reduce its consumption in a certain amount. The controlled device itself will then change its duty cycle in order to obtain the desired reduction. Modern air conditioning units provide this capability but if the controlled device does not do it, an small device that provides it has to be installed within the customer facility. These devices are currently available in the market today for a relatively small price.

6.4 References

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APPENDIX

Study case LV network

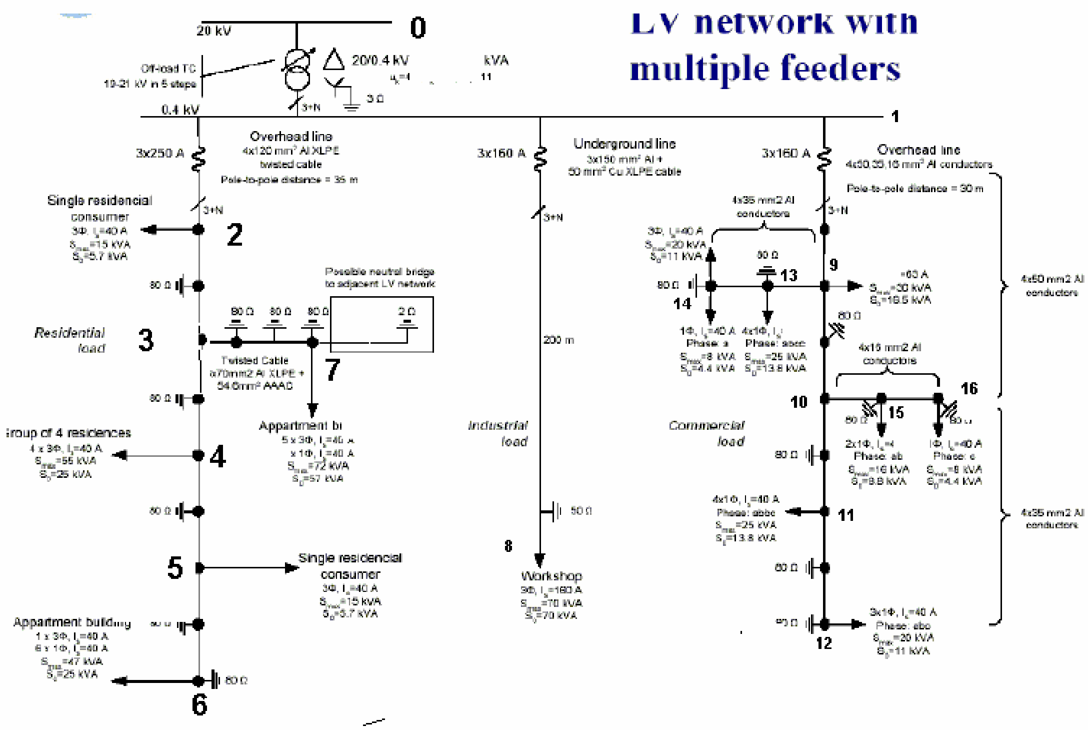

Figure A1.The LV network used for simulations

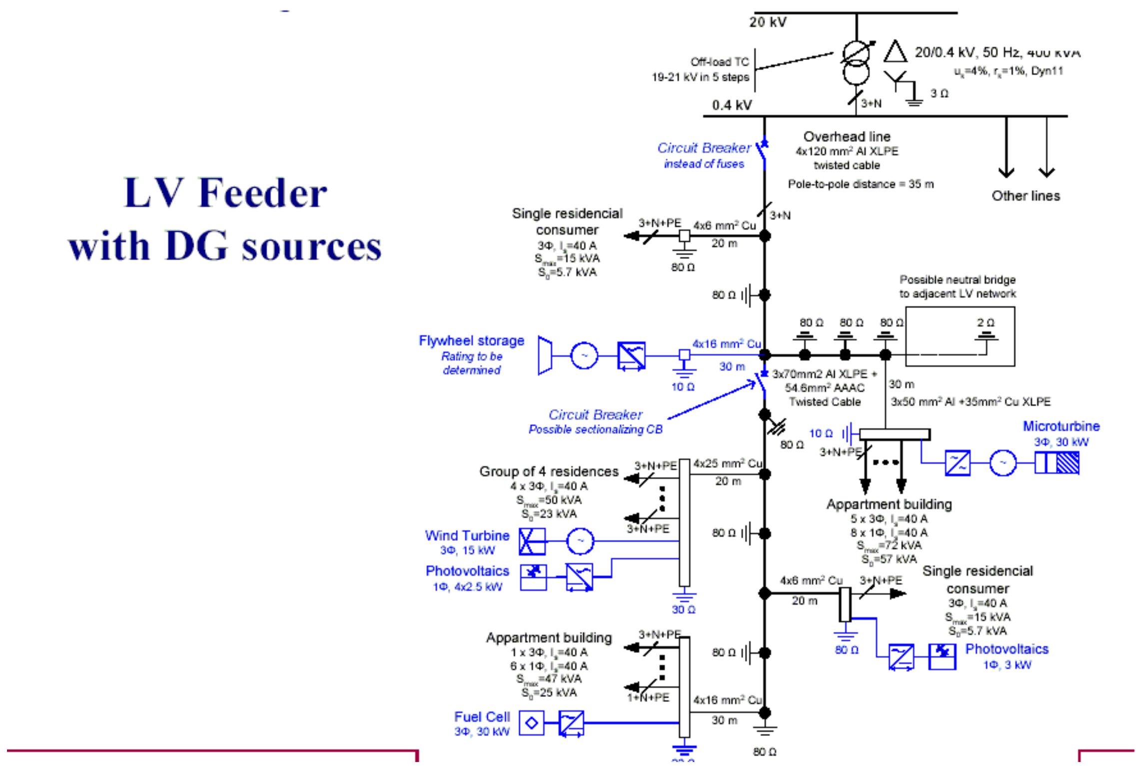

Figure A2. Residential feeder with micro-sources

DATA USED

Data for the units used :

Unit ID	Unit Name	Minimum Capacity (kW)	Maximum Capacity (kW)	Cost Coeff A (ai-Ect/kWh^2)	Cost Coeff B (Ect/Kwh)	Cost Coeff C (Ect/h)	Start Up Cost (Ect)	Start up Time (min)
1	Micro turbine	2	30	0.01	5.16	46.1	5	3
2	FuelCell	1	30	0.01	3.04	130	5	3
3	Wind1	0.1	15	0.01	7.8	1.1	0	<1
4	PV1	0.05	3	0.01	7.8	1	0	0
5	PV2	0.05	2.5	0.01	7.8	1	0	0
6	PV3	0.05	2.5	0.01	7.8	1	0	0
7	PV4	0.05	2.5	0.01	7.8	0.1	0	0
8	PV5	0.05	2.5	0	7.8	1.2	0	0

The values in cost functions are in Eurocents. The values for bi for the Renewable energy sources are the ones that the Independent Power Suppliers with Renewables receive in Greece for selling electricity to the grid. Small values for ai and ci have been used for bias reasons. The value for the Microturbine and Fuel cells are calculated according to the performance of the units and the value of Natural gas 10Ect/m^3.

Renewable power time-series

The following data contains the time-series used as output KW/Installed kW.

Hour	Wind power	PV – timeseries	Hour	WindPower	PV time-series
1	0.364	0	13	0.494	0.318
2	0.267	0	14	0.355	0.433
3	0.267	0	15	0.433	0.37
4	0.234	0	16	0.321	0.403
5	0.312	0	17	0.329	0.33
6	0.329	0	18	0.303	0.238
7	0.476	0.002	19	0.364	0.133
8	0.477	0.008	20	0.373	0.043
9	0.424	0.035	21	0.260	0.003
10	0.381	0.1	22	0.338	0
11	0.459	0.23	23	0.312	0
12	0.390	0.233	24	0.346	0

The time-series used come from the power system of the Greek island of Kythnos where PV and wind Turbines are installed.

Sending Bus	Receiving Bus	R(pu)	X(pu)
0	1	0.0025	0.01
1	2	0.0001	0.0001
2	3	0.0125	0.00375
3	4	0.0125	0.00375
4	5	0.0125	0.00375
5	6	0.0125	0.00375
3	7	0.021875	0.004375
1	8	0.033125	0.00875
1	9	0.0075	0.005
9	10	0.015	0.010625
10	11	0.02125	0.005625
11	12	0.02125	0.005625
9	13	0.010625	0.005625
13	14	0.010625	0.005625
10	15	0.023125	0.00625
15	16	0.023125	0.00625

Table with the line data of the MICROGRID

Hour	Price €/MWh	Hour	Price €/MWh
1	24	13	99
2	17.7	14	149
3	13.01	15	99
4	9.69	16	79
5	3	17	40
6	17.01	18	36.47
7	27.1	19	35.85
8	38.64	20	41.3
9	51.69	21	44.48
10	52.6	22	34.8
11	81	23	30
12	100	24	22.5

Prices of the 6th October 2003 of Amsterdam Power Exchange.