Optimal Integration of Energy Storage in Distribution Networks

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Abstract-- **Energy storage, traditionally well established in the form of large scale pumped-hydro systems, is finding increased attraction in medium and smaller scale systems. Such expansion is entirely complementary to the wider uptake of intermittent renewable resources and to distributed generation in general, which are likely to present a whole range of new business opportunities for storage systems and their suppliers. In the paper, by assuming that Distribution System Operator has got the ownership and operation of storage, a new software planning tool for distribution networks able to define the optimal placement, rating and control strategies of distributed storage systems that minimize the overall network cost is proposed.**

This tool will assist the System Operators in defining the better integration strategies of distributed storage systems in distribution networks and in assessing their potential as an option for a more efficient operation and development of future electricity distribution networks.

Index Terms-- **Distributed Energy Storage, Network Planning, Genetic Algorithm, Dynamic Programming.**

I. Introduction

THE restructuring of the electricity supply market, with the accompanying set of drivers for distribution companies, along with the increasing penetration of distributed energy resources, have raised requirements for new distribution network planning methodologies. The distribution network planning aims at defining the expansion plan and the reinforcements that are necessary to face the natural rise of energy demand, the connection of new customers and distributed generation (DG) [1-3]. Furthermore, the goal of planning is to minimise the sum of CAPEX (capital expenditure) and OPEX (operation expenditure) during a given time period. The solution has to comply with several engineering constraints e.g., on the voltage profile, the maximum exploitation of feeder capacity, the maximum allowable customer minute loss, the maximum allowable frequency of interruptions, etc.

Energy storage, traditionally well established in the form of large scale pumped-hydro systems, is finding increased attraction in medium and smaller scale systems. Such expansion is entirely complementary to the wider uptake of intermittent renewable resources and to DG in general, which are likely to present a whole range of new business opportunities for storage systems and their suppliers [4-6].

Through its potential of balancing fluctuations in the supply and demand of electricity, energy storage can introduce important benefits to the whole electric system. It has a significant impact on both ends of the network: to the generator side, storage has the potential to improve the generator's efficiency and, to the end-user of the network, storage will enhance power quality and reduce peak loads.

In fact, electricity storage devices, located where utility distribution systems are approaching a capacity limit, can provide significant economic assessment. These benefits are associated with deferred or avoided distribution equipment upgrades that often involve a large increment in capacity such as the addition of a second transformer in a substation or refurbishment in a long line segment. If storage is located at critical points in the distribution system, important benefits can be achieved:

- Enhanced service reliability and power quality using active VAR compensation and voltage stabilization;
- Load shifting, using low cost off-peak electricity for resale when electricity prices are higher, thus reducing market risk exposure to volatile on-peak prices and controlling high cost energy imbalance charges ("arbitrage" is the practice of buying at a low price and selling at a higher price at the imbalance market, or the day-ahead market);
- Joule losses avoided by serving peaks with local supply and actively correcting power factor and maintaining system voltages.

Distributed energy storage (DES) might be viewed both as a consumer and producer of power, thereby participating in the market as both a load and generator. Alternatively, storage might be viewed as an integral part of the distribution network, thereby removing it from the normal energy market. This might be linked to the question of who owns storage: load customers, generators, independent storage operators, or the network operator. Regulation concerning the separation of roles in the electricity system varies from place to place and the ownership and operation of storage will vary as a consequence.

In case of independent storage operators, it is worth to notice that energy storage can introduce additional benefits to the network utilities. In fact, it can provide ancillary services, like voltage control, power quality, system reliability, frequency response, spinning reserve.

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If the DSO is allowed to own storage devices, it can profit of DES by compensating possible negative effects caused by the connection of the DG. In fact, in Italy, the connection rules fixed by the Authority force the DSO to accept any request of DG connection with a predetermined connection cost, independently from the effects that DG may have to the network. In particular, energy storage systems are useful with renewable generation, due to their potential capacity to compensate the variability of the power produced.

In the paper, by assuming that DSO has got the ownership and operation of storage, a new software planning tool for MV distribution networks able to define the optimal placement, rating and control strategies of DES systems that minimize the overall network cost is proposed.

This tool will assist the DSOs in defining the better integration strategies of DES in distribution networks and in assessing the potential of DES as an option for a more efficient operation and development of future electricity distribution networks.

II. The Distribution Network Planning Including Energy Storage

In past years the authors have developed a software for optimal network planning [7], based on probabilistic techniques, that allows the optimal planning of MV distribution networks with DG, taking into account expansion over time and usual technical constraints. The optimization procedure minimizes the generalized cost of the network constituted by the CAPEX (investments for new lines, for upgrading existing lines and primary substations, and for network automation) and the OPEX (e. g. losses and maintenance). The optimal solution has to comply with several technical constraints on the voltage profile, the maximum exploitation of assets, the quality of service, etc. The random behaviour of both distributed generation and loads is fully considered with the adoption of a probabilistic load flow.

The aforementioned planning software has two main goals: find the optimal network expansion over time knowing location and characteristic of customers (loads and DG), and optimize the position and the power rate of DG units of different typologies in a given distribution network. In this paper, by exploiting their know-how, the authors have developed a new planning optimization tool that takes advantages of the opportunity of employing DES. By considering a given distribution network with fixed topology during the whole planning period and loads and DG units known through their typologies, locations and power rates, the proposed methodology finds the optimal places and sizes of energy storage devices in order to maximize the network benefits they can introduce, both in technical and economical terms,. The use of storage is limited by constraints on energy reserve, charge and discharge times and efficiency, effect on losses, and hourly energy prices . For these reasons, the daily load and generation curves have to be used and the optimal scheduling of energy resources must be found, based on a daily time scale. In fact, Dynamic Programming (DP) is adopted to solve the DES optimal scheduling problem. Summing up, the procedure may be described as follows:

1. A Genetic Algorithm is used to produce a set of planning alternatives (DES placement and ratings);
2. For each alternative, the DP algorithm is used to define the optimal DES control strategy that minimize the network losses;
3. By using the daily charge/discharge profiles obtained in step 2, the overall network cost (sum of CAPEX and OPEX) is assessed;
4. Based on the overall network costs, the GA evolves the population of solutions and identifies the optimal one.

At the end of the optimization procedure the optimal solution is the one that, complies with the constrains and minimises the global costs finding the best compromise between investments and benefits. The output of the whole optimal planning methodology will be not only the design of the network in the given planning horizon with an indication of CAPEX and OPEX, but also the optimal integration of DES at minimum cost. In addition, the daily scheduling of the storage planned (charge and discharge time intervals) will be provided. In this sense the DES may be regarded as a technology that allows the integration of DG overcoming the existing technical and economical barriers and improving the efficiency of the power delivery.

Focusing on the network benefits that can be achieved, the key point is the evaluation of the amount of DES needed to maximize its potential benefits. This point requires simultaneously solving two problems the identification of the optimal placement of energy storage plants, and the estimation of their optimal sizes. Particularly, regarding the second problem, storage systems have two equally important characteristics: the equipment’s power rating and its discharge duration. The energy storage plant power rating indicates the rate at which the system can discharge the stored energy, generally expressed in kW or MW or, more appropriately, in kVA or MVA. The second characteristic is related to the fact that storage systems must contain enough stored electric energy to operate for as long as needed. Thus, discharge duration is the amount of time that the storage plant can discharge at its rated power without being recharged.

III. Dynamic Programming

Dynamic Programming (DP) is an approach developed to solve multi-stage decision problems and is based on the well known Richard Bellman's Principle of Optimality: “An optimal policy has the property that no matter what the previous decisions have been, the remaining decisions must constitute an optimal policy with regard to the state resulting from these previous decisions” [8]. Actually, this approach is equally applicable for decision problems where multi-stage decision making is not in the nature of the problem but is induced only for computational reasons, as it is the optimization problem at hand. DP tends to break the original problem into sub-problems and finds the best solution of the sub-problems, beginning from the smaller in size. When applicable, DP dramatically reduces the runtime of some algorithms from exponential to polynomial.

DP can be successfully applied when:

- the problem can be divided into stages and a decision is required at each stage;
- a finite number of states is associated with each stage,
- the decision at one stage transforms one state into a state in the next stage,
- there exists a recursive relationship that, provided that the states at stage *j*-1 are known, identifies the optimal decisions to reach the states at stage *j*,
- the recursion for determining the optimal decisions at the stage *j* only depends on the states at stage *j*-1 and not on the way these states have been reached.

The problem of the optimal scheduling of storage to minimize losses and favorite the integration of DG can be solved with DP following the approach used in the hydrothermal coordination. The DP gathers the position and the size of DES in the network from the GA or, that is the same, an individual from the population used for the evolutionary optimization is assessed with the DP to assess the optimal pattern of charges and discharges. A state of the system in the DP algorithm identifies the level of charge in the DES used (a suitable discretization is used to describe the charge of each storage device). The stages or levels in the DP algorithm are the hours of the day. The constraints are the maximum charge and discharge per hour and the invariance of the total charge of each DES at the end of the time interval (the day).

Figure 2 depicts the bottom-up approach used to solve the optimal coordination of DES with DG according to the dynamic programming paradigm. Each state represents a charge level of given set of DES at a certain hour of the day. In order to clarify the process let us suppose that the state β at the D_{II} has to be reached from D_I. Possible states in D_I are α, β, γ, and … η each one labeled with the optimal value of the objective function, L_I, that is related to network losses. It should be noticed that not all the transition from one state in a hour and another one in the successive one are permitted. Generally speaking, those transitions that require a charge or a discharge flow greater than the maximum allowable are neglected. The state β at the level D_{II} is then labeled with the value of the function $L_{II}(\beta)$ that is the minimum value of the objective function calculated considering the couples formed with β and the remaining available candidates. By so doing, the optimal policy to reach β at level D_{II} from D_I is univocally determined (in Fig. 1 the optimal path to β has been assumed through γ). By repeating this procedure for all the states at the D_{II} stage, the optimal policies to reach hour II can be found. The state that minimizes the cost function is simply the one with the smallest label. The optimal policy corresponds to reach the state in D_{II} with the smallest label but it is worth noticing that all the states in D_{II} are reached through an optimal policy. By so doing, each policy to reach D_{III} from D_{II} will necessarily contain optimal sub-policies and the Bellman's Principle will be satisfied. The procedure iterates until the last hour of the day is reached. The final state, the one that has the same charge of the starting hour, is then reached through a sequence of optimal sub policies or, that is the same, the charge-discharge path followed by DES in the day is the one that minimizes energy losses and replace the energy stored in DES

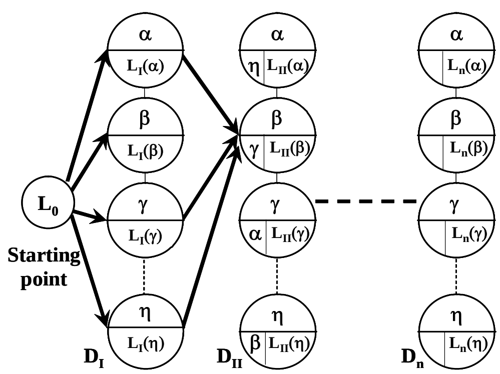

Fig. 1

Fig. 1. Schematic flow chart of Dynamic Programming

IV. Genetic Algorithm for the Optimal Allocation of Storage Units

In the implemented methodology, the network architecture is assumed to be fixed during the planning period, while changes regards load energy demand and power generation, according to appropriate modeled load and generation daily curves. In this context, DES can be a valuable option for the planning engineer to defer or reduce investments for network upgrading [9].

The greater attention should be paid in the siting and sizing of DES because their installation in not optimal locations can result in an increasing of power losses. For these reasons, optimization tools, capable to find the correct siting and sizing of DES units in a given network, can be a valid aid for the planner who has to face with the worldwide growth of DG penetration, mainly for DG units with renewable sources. In the paper, a GA optimization technique has been developed for the optimal DES allocation in MV distribution networks that is deeply described in the following.

A. Coding of the solution

The first important aspect of a correct implementation of the GA is the coding of the potential solution. Considering that the network structure is fixed, all the branches between nodes are known, and the evaluation of the objective function depends only on size, type and location of the DES units. For this reason each solution can be coded by using a vector, whose size is equal to the number of nodes, in which each element contains the information on the presence or not of a storage unit. In order to perform not only the location but also the size of DES, a prefixed number (N_{DES}) of DES sizes have been assumed and classified in input data (e.g. size number 1 corresponds to a 100 kW for 4 hours REDOX storage unit, size number 2 corresponds to a 200 kW for 5 hours ZEBRA storage unit, etc.). Therefore, each element of the solution vector is represented by means of the following alphabet:

0 no DES located in the node;

1, …, N_{DES} size/type index of storage unit installed in the node.

Of course, the vector elements corresponding to the HV/MV primary substations are fixed to 0.

The type of code used is suitable for every kind of network structure (radial, meshed, etc.), that influences only the assessment of the usual technical constraints (voltage profile, thermal feeder capacity and short circuit current limit) considered during the evaluation of the objective function, but does not affect the optimal allocation procedure.

B. GA Implementation

The flowchart of the proposed procedure is shown in Fig. 2. In the first phase, an initial population of possible solutions is randomly generated by means of the following procedure:

- for each solution a value of DES penetration is chosen between 0 and a maximum limit of DES penetration, fixed by the planner on the basis of economical and network security considerations;
- a number of DES units of different sizes is randomly chosen until the total amount of power installed reaches the DES penetration level assigned;
- the DES units are randomly located among the nodes of the network;
- for each DES configuration the optimal profile in terms of charge-discharge is evaluated by using Dynamic Programming (DP)
- a load flow is performed to update the current in each node with storage resources
- the objective function (OF) for each solution is evaluated verifying all the technical constraints; if one of them is violated, the individual is discarded.

Regarding the population size, the best results have been found assuming it equal to the dimension of the problem, i.e. the number of nodes in the network.

In the second phase, the genetic operators are applied in order to produce the new solutions. In the paper the following implementation details for the operators have been considered:

- Selection: the “remainder stochastic sampling without replacement” scheme has been adopted, whereby the number of selections of each individual is calculated in the following way: expected individual count values are calculated as a fraction between the OF value of the individual and the average of OF value of the whole population. Then integer parts of the expected numbers are assigned, and fractional parts are treated as probabilities. For example, a solution with an expected number of copies of 1.4 would receive one sure single copy and another with probability 0.4. This process continues until the population is full.
- Crossover: the “uniform crossover” is adopted, by which each allele is swapped with probability 0.5.
- Mutation: all the vector elements are mutated, according to a small mutation probability, choosing a different value in the defined alphabet.

Each offspring is accepted if all technical constraints are verified and the total amount of DES does not exceed the maximum level of DES penetration.

After several tests, a generational GA model has been implemented, because it seems to guarantee better solutions than the steady state model, even if with a greater number of iterations. Therefore, the offspring replaces all their parents, creating the new population. The procedure terminates when a maximum number of generations has been explored.

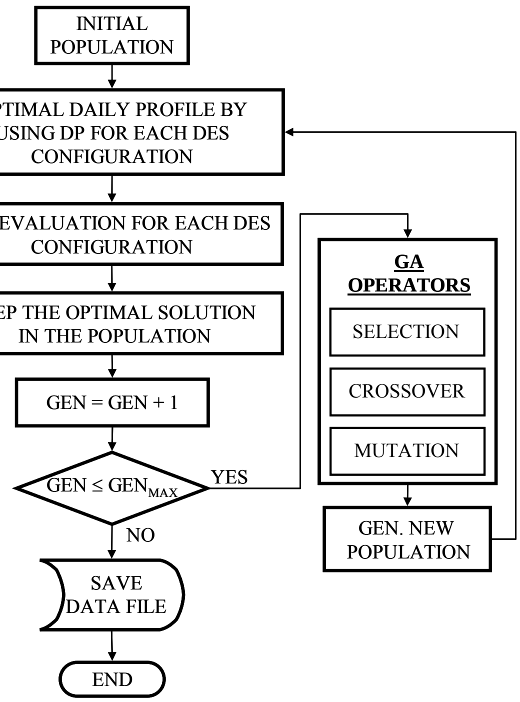

Fig. 2. Flow chart of the optimal DES allocation algorithm.

C. DP nested in the DES optimal allocation procedure

The optimal profile in terms of charge-discharge of each DES is evaluated by using Dynamic Programming (DP). In order to find the optimal delivery and distribution of power a load flow calculation is performed to update the current in each node with DES.

The objective function to be optimized within the technical constraints refers to the total cost of the network which considers the cost of network upgrading and the cost of Joule losses. In fact, the objective function to be minimized in the problem at hand is thus represented by the total cost C_{0G} of the generic network, with present value taken at the beginning of the whole planning period of N years. This cost can be expressed by using the sum:

$$C_{0G} = \sum_{j=1}^{N_{Tot}-N_{Cp}} C_{0j} \tag{1}$$

where N_{Tot} is the number of network nodes, N_{Cp} is the number of substations, N_{Tot}-N_{Cp} the number of branches in the network and C_{0j} the present cost of the j^{th} branch.

The cost of every branch j is the sum of the construction, residual, management costs, and cost of losses in the subperiods, transferred to the cash value at the beginning of the planning period by using economical expressions based on the inflation rate, the interest rate and the load growth rate (all of them constant) [7] .

The cost of every branch can be expressed by using:

$$C_{0j} = C_{0j'} + \sum_{k=1}^{m} C_{0pjk} \quad (2)$$

where C_{0j} is the total cost of the branch j, $C_{0j'}$ the portion of cost independent of power flow, C_{0pjk} the cost term proportional to the power flow through the branch in the k^{th} subperiod (cost of losses) and m is the number of subperiods into which the planning period of N years has been divided.

Denoting with:

- C_{0cj} is the construction costs,
- R_{0j} is the residual value,
- C_{0gj} is the management costs,
- e_j is a binary factor that is equal to 1 for a resized branch and 0 for an existing one.

The cost $C_{0j'}$, independent of power, can be written by using (3):

$$C_{0j'} = e_j \cdot (C_{0cj} - R_{oj}) + C_{0gj} \quad (3)$$

The cost of resizing the j^{th} branch C_{0cj} takes into account the year of reconstruction to transfer the cash value to the beginning of the planning period, while the residual value R_{oj} considers the fact that the planning period does not coincide with the life duration of the component.

The cost of Joule losses in the k^{th} subperiod C_{0pjk} can be calculated transferring, to the cash value at the beginning of the planning period, the annual cost of such losses C_{pjk}, evaluated by using:

$$C_{pjk} = C_{kWh} \cdot (3 \cdot 8760 \cdot coeff \cdot r_j \cdot L_j \cdot ccp_j \cdot I_{jk}^2) \quad (4)$$

where:

- C_{kWh} is the cost of kWh,
- $coeff$ is the utilization factor of energy losses under full load, different for overhead and underground,
- 8760 are the number of hours per year,
- r_j is the resistance per km of line [Ω/km],
- L_j is the branch length [km],
- I_{jk} is the phase current in the j^{th} branch [A] at the beginning of the k^{th} subperiod,
- ccp_j is a corrective coefficient of the losses due to the simultaneity of loads.

In the paper the allocation of DES is based on the normal operation of the network. The use of DES to supply loads during emergency states following network faults is not considered. For this reason, the cost C_{0j} is not included in the DP objective function and the solutions that require any network upgrading are discarded.

For each DES configuration analyzed by the GA, the DP gives the optimal daily profile in terms of charge/discharge of DES considered. Obviously, in DP optimization suitable coefficients have been assumed in order to consider DES efficiency during the charge/discharge phases and opportune constraints in minimum and maximum charge level have been assigned as security margins.

D. The objective function for the DES optimal allocation

The objective function OF to be optimized during a given time period within the technical constraints refers to the total cost C_{0G} of the network already defined in (1), which considers upgrading cost and Joule losses cost, and the cost of installation of DES:

$$C_{OF} = C_{0G} + \sum_{i=1}^{N_{DES}} C_{DES_i} \quad (5)$$

where C_{DESi} is the cost of installation of the DES unit j, and N_{DES} is the number of DES units allocated by GA.

The solution has to comply with several technical constraints e.g., on the voltage profile, the maximum exploitation of feeder capacity, the maximum allowable frequency and duration of interruptions, etc.

V. Results and Discussion

In order to check the methodology described in the paper, a small test network, built on the basis of a real distribution network, constituted by 17 MV/LV nodes and 2 primary substations has been considered (Fig. 3). The network topology is characterized by one existing overhead open loop feeder between the two substations with two overhead laterals. The period taken into account for the planning study is 20 years. This long duration has been assumed only to stress the network, in consideration of its small dimension.

Four typologies of loads have been considered (residential, industrial, tertiary and agricultural), modeled with the daily load curves depicted in fig. 4. For each MV/LV node a constant power demand growth rate of 3% per year has been assumed. Also two existing renewable generators have been included in the network: a 2 MW wind turbine (WT, in node 17) and a 1 MW biomass turbine (BT, in node 11), modelled with typical production curves that take into consideration the

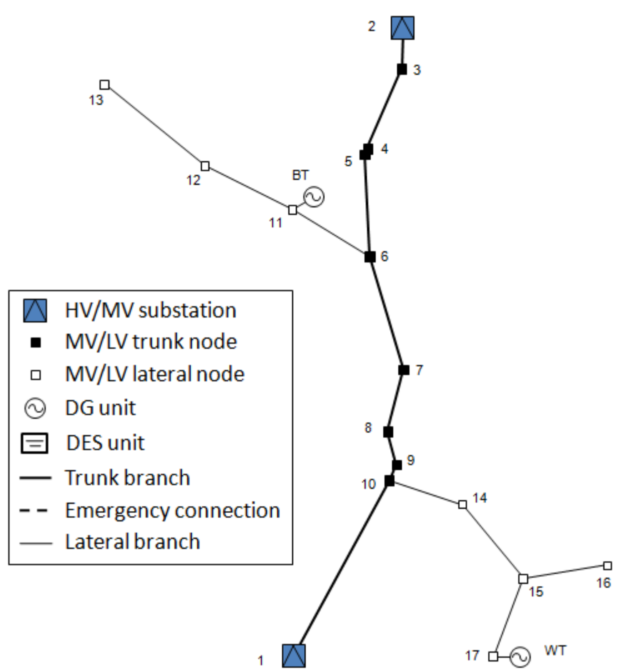

Fig. 3. Test network.

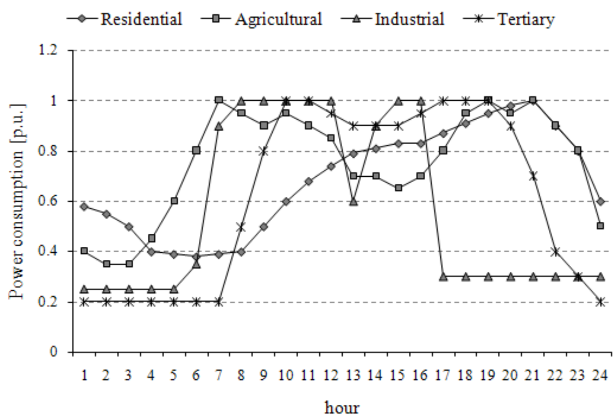

Fig. 4. Daily load curves assumed in the test case.

unpredictability and availability of the primary source (wind, biomass), by means of normal probabilistic distribution function (*pdf*). In particular, the wind generation is modelled with a constant value of the mean output power with high standard deviation, equal in each hour. The biomass DG unit is represented with a firm generation, i.e. with constant output power without uncertainties

Only one type of storage system has been used for the simulations (REDOX battery). The DES sizes chosen and the alphabet of the solution coding used by the GA is illustrated in tab. I. The cost of the storage installation for network application is given on €/kWh or €/MWh, because the DES primary use is to store/supply energy for a long period. Typical per unit costs for REDOX battery are between 150 ÷ 400 €/kWh, with decreasing cost as the energy rate increases. Obviously, this price will be much lower when these systems are produced on large scale. In the paper, due to the small dimension of the test case, the storage installation cost has been disregarded, even if the developed procedure is fully able to consider it.

Firstly, the total cost of the network without installing DES is evaluated. C_{0G} is equal to 545 k€, given by the sum of the cost of network upgrading (C_I = 75.7 k€) and the cost of Joule losses (C_L = 469.3 k€). It is important to notice that the network upgrading is not caused by the load growth during the planning period, but by the presence of the wind turbine that originates some conditions of excessive overvoltage, especially during the night when the power demand is lower.

Then, the proposed optimization procedure has been applied to evaluate the role of DES on this network. The corresponding optimal DES configuration is reported in Fig. 5. Three DES units have been allocated: 2 x 200 kW – 5h Redox batteries in node 12 and 16, and 1 x 300 kW – 5h Redox battery in node 15.

Numerical results (Table II) show that the total cost of the network is reduced by the installation of DES units in the optimal configuration given by the algorithm. In fact, the total cost C_{OF} is equal to 441.9 k€, with the cost of network upgrading reduced to less than one third of the case without DES (C_I = 20.1 k€) and the cost of Joule losses cut by about 10% (C_L = 421.7 k€). The presence of DES has limited the

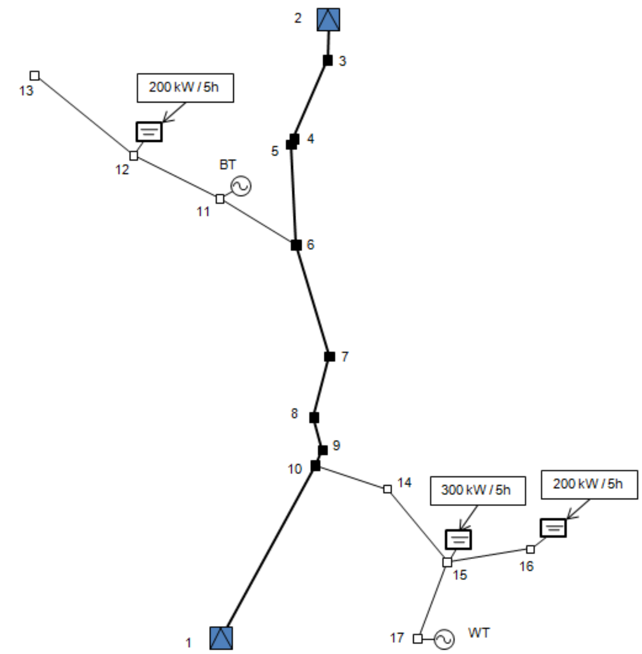

Fig. 5. Optimal network with DES units allocated.

negative effects of the wind turbine, limiting the need to upgrade the network mainly by increasing the demand in the critical hours. The charge/discharge pattern depicted in fig. 6 shows that by charging DES in the off peak hours the network may be operated at less operation costs (less energy losses) and with less capital expenditures (smaller upgrading costs). In fact, the charge periods are concentrated in the first 5 hours of the day, when all the loads considered have low demand (see fig. 4). The general remark is that DES reduces losses by avoiding that excessive power generation may cause reverse power flows in the network. By artificially increasing with DES the load close to intermittent power generation excessive power is used close to DG. Also the need of network upgrading is reduced with DES because the mismatch between power generated and load often causes network refurbishment. Indeed, in the off-peak hours line overload is due to excessive power generation and reverse power flow, in the peak hours overload is caused by high load demand that exploits lines beyond the allowable rated ampacity. DESs are capable to reduce the negative effects caused by the lack of simultaneity between load and generation. In conclusion, the use of DES is very useful to increase the amount of DG in distribution systems without implementing active distribution networks. The DSO has only to control the DES to operate the network without any sharing of responsibilities with producers.

TABLE I
ALPHABET USED FOR CODING THE SOLUTION IN THE TEST CASE

code	DES type	DES size [kW]	Charge time [h]
0		No DES allocated	
1	REDOX	100	4
2	REDOX	200	5
3	REDOX	300	5

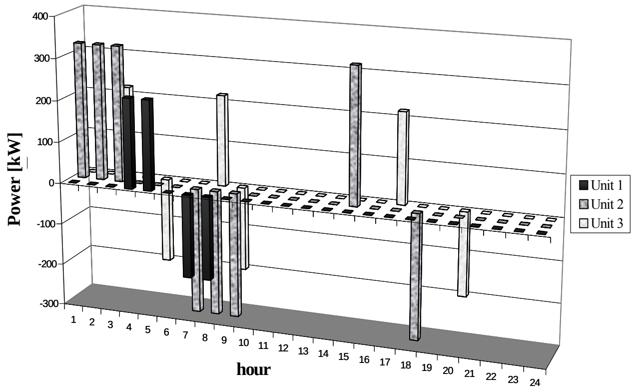

Fig. 6. Optimal daily DES charge/discharge profile.

TABLE II
OF VALUE WITH AND WITHOUT DES SITING AND SIZING OPTIMIZATION

	NO DES	WITH DES
C_I [k€]	75.7	20.1
C_L [k€]	469.3	421.7
C_{OF}[k€]	**545.0**	**466.2**

VI. CONCLUSIONS

In the paper a new planning tool for MV distribution networks is proposed, based on Genetic Algorithm and Dynamic Programming, able to locate the optimal placement and rating of energy storage plants that minimize the overall network cost. The cost includes the capital and operational costs of the allocated storage systems. By so doing, the optimization procedure finds the amount of DES that makes storage the lowest cost option in the network expansion planning process. It is intuitive that the results of the planning procedure depends on the storage technology, due to the differences existing in capital and annual costs, in their power rating and discharge duration ranges, in their life cycles and relative maintenance and replacement costs, etc. Consequently, the proposed planning tool is able to consider the principal energy storage technologies available for network applications.

The proposed procedure considers the presence of DG and to correctly assess the impact that energy storage can have on the capability of the distribution network to accept large amount of DG. Simulation studies performed by the authors have shown that the algorithm permits establishing the optimal distributed energy storage allocation on an existing MV distribution network, achieving the related technical benefits.

VII. REFERENCES

[1] R.C. Dugan and T.E. McDermott, “Distributed generation”, IEEE Industry Applications Magazine, vol. 8, pp. 19-25, March-April 2002;

[2] N. Jenkins, R. Allan, P. Crossley, D. Kirschen and G. Strbac, Embedded Generation, London: IEE publisher, 2000;

[3] H.L. Willis and W.G. Scott, Distributed power generation, New York: Marcel Dekker, 2000;

[4] JA McDowall, Opportunities for electricity storage in distributed generation and renewables, Transmission and Distribution Conference and Exposition, 2001 IEEE/PES;

[5] J. Baker, Electrical energy storage: challenges and new market opportunities, Energy world, 2004, no324, pp. 10-12;

[6] M. Kleimaier, U. Buenger, F. Crotogino, Ch. Gatzen, W. Glaunsinger, S. Huebner, M. Koenemund, H. Landinger, T. Lebioda, W. Leonhard, D. U. Sauer, H. Weber, A. Wenzel, E. Wolf, W. Woyke, S. Zunft, Energy Storage for Improved Operation of Future Energy Supply Systems, CIGRE, International Council on Large Electric Systems, 2008;

[7] F. Pilo, V. Allegranza, G. Celli, R. Cicoria and S. Mocci, “An Integrated Tool for Optimal Active Network Planning”, in Proc. 2003 CIRED Conf., Session 5, paper n. 64;

[8] Larson R. E., Costi J. L.: “Principles of Dynamic Programming”, M. Decker, New York, 1978-1982.

[9] G. Celli and F. Pilo, “Optimal Distributed Generation Allocation in MV Distribution Networks”, in Proc. 2001 22nd PICA Conf., pp 81–86;

VIII. BIOGRAPHIES

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