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Optimization of Power Flow with Energy Storage Using Genetic Algorithms

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Abstract— **This paper applies genetic algorithms to optimize the operation of a transmission network with energy storage capabilities, to optimize its costs, which include both generation and storage costs, for cases when the data inherent to the system is assumed to be perfectly known. The problem is formulated through the DC optimal power flow equations, including losses across the transmission lines, therefore allowing solutions regarding the network generation costs to be obtained, with and without storage. In this way, the financial impact inherent to the usage of energy storage can be derived. Since we are dealing with a large combinatorial problem, the search throughout the solution space was done by means of the Genetic Algorithms. The solutions consist of the storage device's charging or discharging rate at which it must be operating during each sub-interval considered for the simulations. The results delivered by the GA have proven the profitability of including energy storage capabilities in the transmission network of São Miguel (Portugal) and the usefulness of such algorithm in a real world application.**

I. INTRODUCTION

PUMPED HYDRO ENERGY STORAGE (PHES) is the most used energy storage technology for high-power applications [1]. It consists of pumping water from a lower reservoir to an upper reservoir during low power demand periods. During high demand periods, the water is discharged from the upper reservoir to the lower one and generates electricity by means of a turbine. Therefore, the correct usage of a storage device can lead to a lesser dependency on fuel based generators and yield significant cost savings.

The scheduling of storage units in transmission networks has been the object in several works. A conventional methodology is to apply Lagrangian Relaxation [2] [3] extended to the problem with energy storage units in order to turn the non-convex optimization problem into a set of convex subproblems, coordinated by Lagrange multipliers. However, the solutions to these sub problems may vary between maximum and minimum generations by changing slightly the multipliers. Dynamic Programming (DP) [4] [5] [6] [7] was also used to search the solution space for the global optimum in some works when the need of scheduling energy storage units is present. However, when dealing with large-sized problems with too many variables, this method becomes limited, since a high computational time and memory storage are required. Furthermore, the global optimum is not guaranteed [8]. Evolutionary computing methods are promising for the scheduling problem. Some works employ Genetic Algorithms (GA) [9] [10], Particle Swarm Optimization (PSO) [11] [12] and Evolutionary Programming (EP) [13], where the results offered are reported to be reliable due to the fact that such methods allow a very broad search throughout the solution space to this large combinatorial problem.

The usage of GA has returned satisfactory results in a short period of time in the cited works above and it allows a suitable representation of the solution space [14]. Therefore, GA was used in the present work to search the solution space for the schedule that yields the minimum sum of both the generation costs and the costs inherent to the storage of energy, when transmission losses are present. The case study was the transmission network in São Miguel, Açores, Portugal, since a Pumped Hydro Energy Storage Power Plant (PHESPP) is yet to be implemented in this network in the near future.

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II. PROBLEM FORMULATION

In order to obtain the operation costs of the network under a certain schedule, the DC Optimal Power Flow (DC OPF) can be employed to obtain the combination of generators outputs that yields the lowest operation cost, according to the demand levels and the configuration of the network. We will start by introducing the standard deterministic DC OPF problem without energy storage.

A. DC Optimal Power Flow without Energy Storage

Adopting the same methodology as in [15], the standard DC OPF for a generic instant of time, for the deterministic case, is formulated as follows, considering active power losses across the lines:

$$\min_{\theta, p_g} \quad \sum_{i \in \mathcal{G}} c_{g_i} p_{g_i} \tag{1}$$

s.t.

$$p_{g_i} - \sum_{m \neq i} (p_{im} + \frac{1}{2} h_{im}) = d_i \tag{2}$$

$$h_{im} = 2 g_{im} \theta_{im}^2 \tag{3}$$

$$p_{im} + b_{im}(\theta_i - \theta_m) = 0 \tag{4}$$

$$|p_{im}| + \frac{1}{2} h_{im} \leq \bar{p}_{im} \tag{5}$$

$$\underline{p}_{g_i} \leq p_{g_i} \leq \bar{p}_{g_i} \tag{6}$$

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Equation (1) describes the minimization of the operation costs, where $\mathcal{G}$ is a set of generation nodes, c_{g_i} is the generation cost per MWh from the energy source $i \in \mathcal{G}$ and p_{g_i} is its power output.

Equation (2) specifies that the power balance in a generic bus *i* must result in supplying that bus with its demand and (3) expresses the losses across the transmission lines. Equation (4) simply translates what the power flow between two generic nodes must be equal to.

In (5), we're constricting the power flow between two buses to a limited amount that depends on the conductors linking them. (6) constrains the power output from a generator bus to between its minimum input and its maximum capacity.

B. DC Optimal Power Flow with Energy Storage

The inclusion of storage units adds additional constraints to the problem, since these units can only store a certain amount of energy and may have limited charging or discharging rates. Moreover, while the classical OPF problem without storage consists in a static evaluation of the network (optimizing the objective function for a specific fixed time), the inclusion of a storage node induces a correlation across time, since the operation of a storage unit in a certain interval of time will influence the outcome during the periods after. In this section, we extend the formulation presented in [16] and include the active power losses and constraints regarding the storage units. The objective function considered here is the total operation cost of the network.

Considering the losses in the transmission lines, the DC OPF problem with a certain number of storage units in the network is formulated as follows:

$$\min_{\theta, p_g, s} \quad \sum_{t=1}^{T} \Big(\sum_{i \in \mathcal{G}} c_{g_i}(p_{g_i}(t), t) + \sum_{k \in \mathcal{S}} s_k(w_k(t), r_k(t)) \Big) \tag{7}$$

s.t.

$$p_{g_i}(t) + r_i(t) - \sum_{m \neq i} (p_{im}(t) + \frac{1}{2} h_{im}(t)) = d_i(t) \tag{8}$$

$$h_{im}(t) = 2 g_{im} \theta_{im}^2(t) \tag{9}$$

$$p_{im}(t) + b_{im}(\theta_i(t) - \theta_m(t)) = 0 \tag{10}$$

$$|p_{im}(t)| + \frac{1}{2} h_{im}(t) \leq \bar{p}_{im} \tag{11}$$

$$\underline{p}_{g_i}(t) \leq p_{g_i}(t) \leq \bar{p}_{g_i}(t) \tag{12}$$

$$w_k(t) = \begin{cases} w_k^0 - r_k(t)\Delta t & \text{if} \quad t = 1 \\ w_k(t-1) - r_k(t)\Delta t & \text{if} \quad t > 1 \end{cases} \tag{13}$$

$$0 \leq w_k(t) \leq W_k \tag{14}$$

$$-\bar{q}_k \leq r_k(t) \leq \bar{f}_k \tag{15}$$

In (7), $\mathcal{S}$ is the set of storage nodes in the network. $c_i(p_{g_i}(t), t)$ is the generation cost per MWh and depends on the generator's power output during the period t, as well as on the specific period, in a generic way. $w_k(t)$ is the accumulated energy by the storage unit at the end of period t and $r_k(t)$ is the power draw during this period (if positive, the storage node is supplying the network with a power output; if negative, it stores energy). Therefore, $s_k(w_k(t), r_k(t))$ is the storage cost during the period t, which in a generic way depends on w_k and r_k. T is the number of periods the problem is solved for.

Equation (8) is the power balance in a node *i*, as explained on the previous section, but now including the power draw r_i, in case the node *i* is an energy storage unit.

As for the storage constraints, (13) relates the storage node's charged energy in a period with the power draw during that period (multiplied by the length of the time period Δt) and the previously stored energy (w_k^0 is the stored energy at the beginning of the simulation). (14) assures the stored energy can't be either negative or superior to the maximum storage capacity (W_k). (15) limits the power draw inferiorly to its maximum storing rate ($\bar{q}_k$) and superiorly to its maximum generating rate ($\bar{f}_k$).

III. Genetic Algorithms in Pumped Hydro Energy Storage Scheduling

GA consists in a mechanism of natural selection, meaning that fittest individuals are most likely to be winners within a competitive environment. Such algorithms are widely used in large combinatorial integer problems [17], since being a metaheuristic makes it prosecute a very broad search of the solution space. The modelling of the problem under study fits these characteristics and its performance in pumped-storage devices' scheduling is reported in some studies to deliver reliable results [9] [10] in a satisfactory amount of time [18], in comparison to other algorithms.

A. Solution Encoding

When applying a GA to a specific problem, the first step is to represent each solution by means of a chromosome - a set of genes, where each gene contains a fixed value related to the decision variables. In the specific case we're dealing with, the PHESPP to be analysed can only be either charging or discharging energy at a certain period of time, which simplifies the problem. We need to know whether the PHESPP should be pumping the water into the reservoir or discharging the water from the reservoir and at what rate. In the present work, we extend the solution encoding done in [14] to our specific case, which consists of 5 pumps and 3 Pelton turbines. The solution encoding we adopt is illustrated in Figure 1.

For our case study, each individual is represented by means of 24 genes, since we're performing the day-ahead schedule of the PHESPP using time periods of 1 hour.

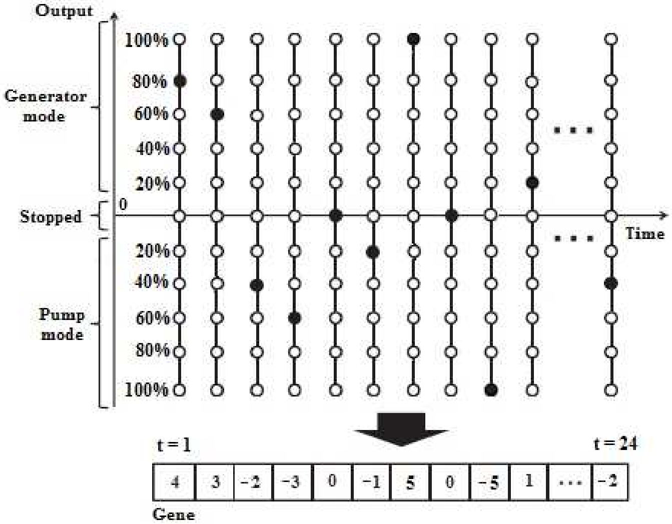

Fig. 1. Solution Encoding Used for the Present Case Study

B. Solution Decoding

In order to determine the minimum operation costs of a transmission network under a certain PHESPP schedule, the solution space search must return the outputs from the energy sources during the periods of time so a fitness can be derived, along with the costs associated to the operation of the storage device. In the present work, during periods the storage device is charging or discharging, we're treating it as a demand bus with a fixed load equal to the charging rate or a generator bus with a fixed output equal to the discharging rate, respectively. In the case the device is idle, we treat it as a bus which is neither generating nor demanding energy. We are interested in obtaining the minimum of the total cost over sequent periods of time. Since a fixed schedule makes it such that the generators operate independently among the different periods, the problem formulated in (1) can be solved for each period. Therefore, the sum of the minimum operation costs in every period becomes the minimum operation costs over sequent periods of time, which is what we intend to obtain.

C. GA Operators

The fact that this problem has a limited space of feasible solutions, due to the reservoir's capacity, some care must be taken when performing the operations to the solutions. The considered space of feasible solutions was every solution that doesn't result in having a negative amount of stored energy, or an amount of stored energy that doesn't exceed the reservoir's capacity.

1) Initial Population: An individual is created by simply generating one gene at a time randomly, starting at the gene corresponding to the first period of the simulation, and every time a gene is generated, the existing partial chromosome's feasibility is checked. If at any time a generated gene results in an infeasible partial chromosome, that gene is generated again until feasibility is reached.

2) Selection Method: After evaluating the fitness of an entire population, a new generation must be created. For this, pairs of individuals must be selected, so that the crossover operator must be applied. The selection method used for individuals to mate was Tournament Selection [19], where a number of individuals equal to a defined value s are selected and listed in descending order of fitness. This list is run and for each individual, a random number between 0 and 1 is generated. If this number is lower than a defined probability, that individual enters the mating pool and the tournament is reset. If no individual is selected by means of this random criteria, the last individual of the list is selected. After the number of parents reaches the population size, we proceed to the crossover operator.

3) Crossover: The selected operator for the problem we're dealing with was uniform crossover, rather than the k-point crossover [20], since this last one doesn't play well with the problem we're dealing with due to the fact that portions of the chromosome are swapped. This most likely would make it very difficult to create feasible children. With uniform crossover, every time an allele swap is to happen, the resulting children are checked for feasibility. If they don't pass, that swap simply doesn't occur and we move on to the next allele. After doing this for all the pairs of parents, we proceed to the mutation operator.

4) Mutation: Mutation can be advantageous to avoid convergence to a local optimum. It consists in randomly altering a gene to a different value [20]. By doing so, bringing the individual out of the feasible space of solutions might occur. Therefore, to implement this operator in the problem we're dealing with, when mutation is to occur in an allele, the options for feasible values for that allele to have are checked first. Then out of those values, one of them is selected randomly. Obviously, if there's no possible altering for a randomly selected allele, no mutation will occur.

5) Elitism: The odds of the individual with the best fitness value being selected to enter the mating pool are high. However, if selected and after applying the crossover to it, the resulting children might possess a worse fitness value. If so, we lose the individual and therefore there's a chance that none of the individuals in the new generation has a fitness as high, or higher, than the lost individual. That's where the elitism operator comes in handy [20]. By defining the number k of individuals we want to preserve, we check the fitness of the worst k members of the new generation. Shall it be worse than the fitness of the k best individuals of the previous generation, a swap occurs and therefore we preserve the individuals, making sure that potential solutions aren't destroyed.

IV. Case Study: Transmission Network in São Miguel

The intended analysis was conducted on the transmission network in São Miguel. Data concerning the existing generators nowadays in this network can be found in Table I.

TABLE I

Transmission Network in São Miguel - Generator Nodes [21]

Generator Node	Energy Source	Generator Groups	Capacity (MW)
CTCL	Thermal (Fuel Oil)	4	67.28
		4	30.784
CGRG	Geothermal	4	16.6
CGPV	Geothermal	1	13
PEGR	Wind	10	9

Judging by the information present in [22] regarding the geothermal energy production during 2012, output fluctuations from the geothermal energy sources were neglected, meaning that for this case study, the power injections from the generator nodes CGRG and CGPV were considered constant. As for the output of the thermal power plant (CTCL), it was considered that its minimum output is 12 MW, which is also assumed in [22]. The actual network is to be expanded to the configuration shown in Figure 2.

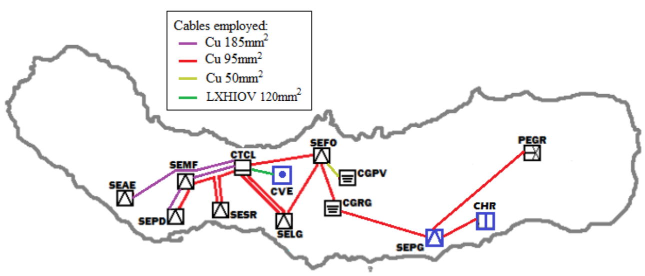

Fig. 2. Transmission Network in São Miguel with Energy Storage [21]

The upgrades to the existing network include:

- A waste-to-energy power plant (CVE node, see Figure 2), which is meant to inject a constant power of 6.84 MW in the network during high demand periods of the day and 4.33 MW during low demand periods and during the whole weekend [22].
- Construction of a PHESPP (CHR node, see Figure 2), with a maximum pumping capacity of 10.5 MW, a maximum generation capacity of 11.5 MW and 57 MWh storage capacity [22].
- Construction of the substation SEPG (see Figure 2) to be part of the transmission network. [21].
- Construction of a transmission line to connect SEPG to CGRG [21].

Data concerning the distances between linked nodes, as well as their per unit parameters, can be found in Table II.

TABLE II

Data concerning the connections between nodes [21]

Bus i	Bus j	R p.u.	X p.u.	Cap. (MW)
CTCL	SEMF	0.0158	0.061	56.12
	SELG(1)	0.0318	0.0641	37.41
	SELG(2)	0.0318	0.0641	37.41
	SEFO	0.0559	0.1128	37.41
	SEAE	0.0262	0.1012	56.12
	SESR	0.0226	0.0457	37.41
	CVE	0.0233	0.0084	14.81
CGRG	SEFO	0.0255	0.0515	37.41
	SEPG	0.0448	0.0904	37.41
CGPV	SEFO	0.0176	0.0168	12.47
PEGR	SEPG	0.071	0.1433	37.41
SEMF	SEPD(1)	0.0056	0.0216	56.12
	SEPD(2)	0.0112	0.0226	37.41
	SESR	0.0361	0.0729	37.41
SELG	SEFO	0.048	0.097	37.41
SEPG	CHR	0.026	0.0565	37.41

In the present work, the generation costs were assumed to be linear and time invariant. The thermoelectric power plant in the transmission network under study operates by means of combustion diesel engines. According to estimates derived in [23], the production cost of electricity for such power plants, considering moderate fuel prices, ranged between 100 and 125 €/MWh in 2007. As for wind on-shore, generation costs ranged from 75 to 110 €/MWh. Such costs from this source include investment costs, fixed and variable operating costs and, when applicable, fuel and emissions related costs. In the transmission network under consideration, the thermal power plant is significantly old, while the wind power plant is relatively recent. Therefore, for the thermal energy source, we're neglecting the costs related to the investment and a cost of 93€/MWh is being used. For the wind energy generator, a cost of 90€/MWh is being utilized, so as to keep it lower than that for the thermal energy and to make both these sources cost competitive at the same time. As for the remaining generators, since the power output from the geothermal and waste-to-energy power plants is the same throughout the days regardless of the power demand, their generation costs are the same either with or without storage and they are not being included in the operation costs.

As for the PHESPP, the project option for the network in São Miguel was obtained from [24], which operates by means of five pumps and three Pelton turbines, with efficiencies of 89% and 88% for charging and discharging, respectively. The results obtained by the author for a 10MW generation application with an 8 hour generation cycle (close to the case under study) and operating 250 days a year (assumed to be the same in our case) are nearly 0.05 USD/kWh. Therefore, the cost considered in this case study was 40€/MWh. Since in this particular case the pumps and turbines have a considerably low maximum power, start up costs for the charging and discharging cycles were neglected.

V. RESULTS

The data used for the power demand evolution during a day was the one occurred in 2012 for different typical days. We are presenting the results referring to the load curves occurred in a specific day both in the Summer and Autumn seasons, because these curves have different demand levels, thus originating different outcomes for the network operating with energy storage. In the simulations performed, the GA was run 30 times. For each iteration, the stop criterion was established as 400 generations or 100 generations without fitness improvement.

Table III contains the results obtained by the day-ahead schedule for the Summer day, for different values of population size ($\mathbf{P_z}$), mutation rate ($\mathbf{M_r}$), crossover rate ($\mathbf{C_r}$) and elitism. They are expressed in terms of cost savings yielded by the usage of the storage device in the network. The time consumed by all the 30 simulations for each combination of parameters is also presented.

TABLE III
GA STATISTICAL RESULTS FOR SUMMER DAY

$\mathbf{P_z}$	$\mathbf{M_r}$	$\mathbf{C_r}$	**Elitism = 1**				**Elitism = 2**			
			Cost Savings (€)			**Time (min)**	**Cost Savings (€)**			**Time (min)**
			Max	**Mean**	σ		**Max**	**Mean**	σ	
80	0.15	0.6	1290	969	183	12.06	1192	907	236	12.11
		0.9	1187	929	214	11.65	1285	1000	179	12.73
	0.25	0.6	1307	1136	146	16.41	1317	1160	146	17.4
		0.9	1318	1186	109	15.07	1316	1190	87	15.84
100	0.15	0.6	1227	995	179	16.48	1279	1004	166	15.75
		0.9	1218	1028	193	15.34	1194	1053	123	15.83
	0.25	0.6	1316	1213	70	19.2	1318	1180	106	17.89
		0.9	1314	1169	82	17.86	1317	1183	76	18.8
150	0.15	0.6	1287	1125	115	25.07	1315	1122	174	27.08
		0.9	1313	1117	135	25.03	1318	1113	111	24.23
	0.25	0.6	1318	1218	77	26.77	1318	1212	97	25.03
		0.9	1318	1208	86	30.13	1318	1239	65	27.87
200	0.15	0.6	1318	1205	70	32.96	1317	1161	107	34.47
		0.9	1317	1189	96	35.31	1318	1173	89	37.94
	0.25	0.6	1318	1237	71	36.36	1318	1234	75	35.02
		0.9	1318	1239	68	36.49	**1318**	**1250**	**76**	**35.43**

It can be noticed that the population size has a considerable influence on the mean of the cost savings obtained. Another relevant parameter is the mutation rate, since taking such a rate of 0.25 yields better results in terms of mean and standard deviation, regardless of the other parameters. As for the crossover rate, it doesn't appear to be very relevant, according to the results obtained for this day. The elitism value is also not very relevance. Selecting the parameters $\mathbf{P_z} = 200$, $\mathbf{M_r} = 0.25$, $\mathbf{C_r} = 0.9$ and elitism = 2 would make it such that the maximum found lies within the standard deviation centred at the mean. However, for a matter of computational effort reduction, $\mathbf{P_z} = 150$ should be taken into consideration, keeping the remaining parameters the same.

Statistical results obtained for the Autumn day can be found in Table IV. For this day, the solution is more trivial than that for the Summer day. It can be noticed that the set of parameters $\mathbf{P_z} = 80$, $\mathbf{M_r} = 0.25$, $\mathbf{C_r} = 0.9$ and elitism = 1 performs well enough, judging by the maximum found, mean and standard deviation obtained.

The schedules found that yielded the results just presented are shown in Figures 3 and 4, for the Summer and Autumn days, respectively. The power demand curve and the power outputs from the thermal and wind generators are also presented, with and without energy storage.

TABLE IV
GA STATISTICAL RESULTS FOR AUTUMN DAY

$\mathbf{P_z}$	$\mathbf{M_r}$	$\mathbf{C_r}$	**Elitism = 1**				**Elitism = 2**			
			Cost Savings (€)			**Time (min)**	**Cost Savings (€)**			**Time (min)**
			Max	**Mean**	σ		**Max**	**Mean**	σ	
80	0.15	0.6	1052	826	190	9.89	1052	788	188	9.1
		0.9	1052	845	122	7.82	1052	849	164	9.43
	0.25	0.6	1052	978	77	9.57	1052	975	95	9.98
		0.9	**1052**	**989**	**72**	**9.55**	1052	972	84	9.2
100	0.15	0.6	1052	849	169	9.23	1052	818	194	11.4
		0.9	1052	863	142	9.98	1052	927	125	12.87
	0.25	0.6	1052	974	126	12.07	1052	999	69	12.25
		0.9	1052	970	74	11.41	1052	993	91	12.92
150	0.15	0.6	1052	957	96	15.72	1052	964	60	16.77
		0.9	1052	978	70	15.41	1052	938	102	15.01
	0.25	0.6	1052	1006	68	14.24	1052	1027	53	17.16
		0.9	1052	1026	55	16.16	1052	1023	50	14.6
200	0.15	0.6	1052	997	84	21.22	1052	986	64	24.17
		0.9	1052	982	59	18.84	1052	1000	69	23.16
	0.25	0.6	1052	1040	37	19.42	1052	1045	27	22.04
		0.9	1052	1036	44	17.5	1052	1041	34	19.69

The more inferior the load is during low demand periods, the more energy can be charged without raising the thermal or wind generators' output, to posteriorly be delivered to the network during high demand periods. By comparing the demand profiles of both presented cases, it can be inferred that the Autumn day has more potential to store energy in comparison to the Summer day. However, the Autumn day has a limited need for energy supply during high demand periods (both thermal and wind generators are reduced to their minimum outputs). The need to store energy during this day becomes reduced in comparison to the Summer day, making this last one more profitable, even though it has less potential to store energy.

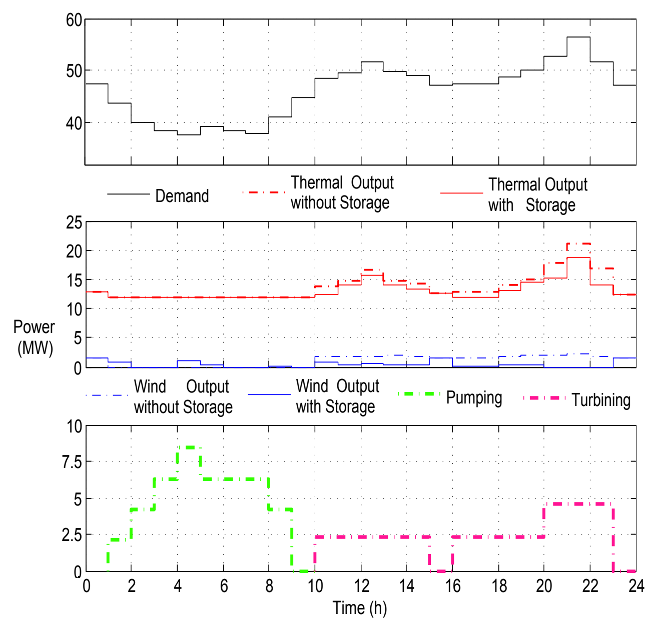

Fig. 3. Best Schedule Found for Summer Day

It's interesting to notice, however, that the usage of storage capabilities in the network under analysis makes it such that the output from the wind energy source is lowered in some intervals, rather than having solely the thermal energy source output diminished. This happens because the cost for wind energy generation used for the simulations is not low enough, compared to the thermal energy generation cost. The geographical configuration of the network (see Figure 2) implies that considerably larger power losses occur when transmitting power from the wind source to most of the network substations, in comparison to transmitting the same power from the thermal source, making both these sources cost competitive.

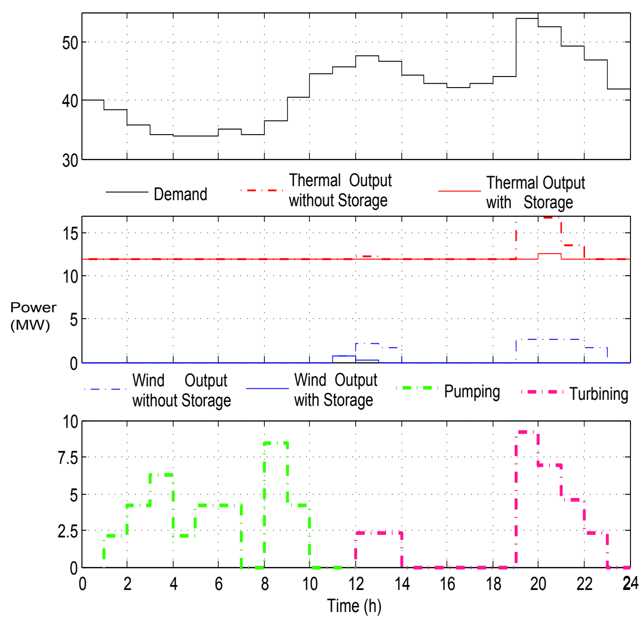

Fig. 4. Best Schedule Found for Autumn Day

It can also be noticed in Figure 3 that there is a preference in turbining at higher rates for the demand peaks and therefore reducing the thermal generator output by a larger quantity during the respective periods, rather than just uniformly reduce such output by the same quantity over the whole curve. The power transmission between two buses is proportional to the difference in voltage angles between them. Then, the higher the power transmission between buses, the larger the voltage angle between them. However, the losses associated to these power flows are proportional to the square of the difference between voltage angles. This means that by diminishing the power flow between buses for high demand periods results in a greater reduction of power losses, in comparison to doing so for low demand periods, yielding greater cost savings. This is especially notorious in the thermal source output curve, since there is a considerable variation in its power intensity throughout the day. Since the wind source power output remains at low values the whole day, the difference in power losses avoided throughout the day is not as significant.

What was presented in Figures 3 and 4 confirms that the Autumn day has a more trivial solution in terms of search than the Summer day, which justifies the need of a bigger population size required for good statistic results for this case (see Tables III and IV).

VI. Conclusions

The developed work consisted in obtaining the optimal financial outcome yielded by the correct usage of a storage device in a transmission network, by searching the possible schedules using Genetic Algorithms, considering both the generation costs and the costs to store energy, and taking into account the losses across the transmission lines.

The results obtained have shown that by using storage capabilities in a network may lead a renewable energy source to have a lower penetration, which in our case was due to the inclusion of power losses, making it cost competitive with a non renewable source. Such consideration of power losses has also proven to influence the scheduling problem in terms of turbining rates. Nonetheless, it was shown that for the particular network under analysis, the good usage by means of scheduling of the storage device yields significant daily cost savings. It can also be concluded that the choice of the appropriate GA parameters strongly depends on the shape of the curves, particularly the population size, which is the parameter of most relevance not only in the computational effort, but also in the quality of the statistical results.

For the same time horizon, the GA solution encoding employed in the present work can be extended to longer periods of time (less genes), naturally leading to a lower computational effort, but also to less accurate results. The selection of the appropriate period length must be a trade off between these facts.

VII. Acknowledgements

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