Genetic Algorithm Based Energy Demand-Side Management

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***Abstract*—Application of demand-side management (DSM) plays today an important role in energy management both in industrial and residential domain. This paper proposes a generic approach to DSM which is based on the genetic algorithm (GA), as one of the powerful search heuristics inspired by the process of natural evolution. The proposed approach was defined flexibly enough to be capable of discovering an optimal load distribution (e.g. from the financial perspective) in practically any multiple energy supply/multiple load facility infrastructure. Optimization of the demand side was carried out by taking into account the forecasted energy demand and applied tariff schemes as well. Furthermore, a performance of the proposed approach was verified at a multiple supply/multiple load use case scenario. Based on the optimization results, it was concluded that the proposed GA based solution could be successfully utilized to facilitate decision making of energy managers regarding the appropriate DSM measure selection.**

I. Introduction

For many years demand-side management (DSM) has been utilized in order to answer the needs of mostly large and predictable loads in the industry domain [1]. Today, DSM concept plays an important role in management of the energy consumption of smaller commercial and residential end-users. The reason for this is strong energy supply constraints which are forcing the utilities to take into account the DSM potential. In fact, it is more profitable and environmentally beneficial to perform the energy demand management by investing into the facility infrastructure and by applying corresponding load management measures, rather than increasing the energy generation and transmission capacity. Moreover, the DSM measures are aimed to lower the energy supply and distribution requirements. In the same time, by applying the DSM measures, it is possible to answer the needs of much higher number of end-users with the same energy supply capacity.

Various optimization paradigms were utilized so far to solve the problem of discovering an optimal end-use load distribution and applying adequate DSM measures. One of the most popular and often cited approaches to apply optimal resource and load management is based on the use of genetic algorithm (GA) [2]. Until today, many papers on this topic were published in the literature [3]-[10]. For instance, online management of fuel cells was proposed in [3], [4] for onsite provision of the energy supply to residential loads. Proposed approach was based on the artificial neural networks (ANN), while GA was used for the offline extraction of the training database using different load demands. In [5] GA was used to minimize the energy consumption for operating the refrigerated warehouse supported by wind energy. On the other hand, [6] proposes a modified GA approach for scheduling of generator units in order to meet the forecasted load demand at minimum cost. Development of hybrid techniques was carried out in [7] for short-term generation scheduling based on the GA approach in order to adjust the pre-scheduling results obtained by ANNs. Moreover, matrix real-coded GA optimization module was described in [8] to perform the load management within a smart energy management system aimed for optimization of the micro-grid. Approach proposed in [9] was composed of a master and slave GAs to optimize the scheduling of direct load control strategies. Finally, in [10] a GA based decision support information system was analyzed which would, apart from the equipment scheduling, facilitate dealing with the various load management scenarios.

In this paper, a generic approach to DSM was proposed which was based on the GA paradigm. The proposed GA based approach was defined in such a way to discover an optimal load distribution profile (for instance from the financial perspective) in practically any multiple energy supply/multiple load facility infrastructure. This is contrary to the already existing methods which are in some cases closely tied to a specific facility infrastructure and given resources. The main idea of the proposed approach was to suggest the appropriate DSM measures to the energy manager, by taking into account the forecasted energy demand and applied tariff schemes. Having in mind the complexity of this task, the proposed solution was leveraged on the GA paradigm as one of the powerful search heuristics which was utilized to search for the optimal energy demand. Both single, as well as multiple loads optimization is supported depending on the given use case scenario and the facility infrastructure. Furthermore, one time step, but also the entire time span of the given time interval is supported for performing the DSM optimization. Through the proposed approach, different DSM measures (such as curtailing and/or shifting the load) could be taken into the consideration solely or in combination to avoid for instance peak hours or high tariff periods. By defining the desired optimization constraints of the proposed solution, it is possible to vary the degree of influence on the end-user operation, to preserve the total energy consumption per load etc. In order to evaluate the performance of the proposed approach, GA optimization procedures were carried out for a simple use case scenario having two energy carriers at the supply side, renewable energy sources (RES) and two loads at the demand side.

The remainder of this paper is organized as follows. Section 2 describes the concept of the DSM measures and their potential application. The following Section 3 analyzes the proposed GA based approach to DSM. The same section tackles the problem of GA optimization objectives, constraints and parameters definition suitable to satisfy the demand side having in mind the applied tariff schemes. Optimization results and performance of the proposed approach are analyzed and discussed for a simple use case scenario within Section 4. Section 5 presents the final conclusions of this paper.

II. Concept of Demand-Side Management

The main objective of DSM is to change the energy end-use, i.e. to influence the energy consumption profile in order to reduce the overall cost of the consumed energy [11]. In other words, DSM represents the corresponding modification of the consumer's energy demand by applying various mechanisms mainly driven by the financial incentives. DSM related measures are often undertaken by the end consumer, but also can be initiated by the distribution utility itself. It usually includes actions such as increasing or decreasing load demand, shifting it from high to low tariff periods if variable tariff scheme is applied (e.g. moving the energy use to off-peak periods such as during the nights, weekends) etc. DSM can be applied through:

1) energy efficiency improvement and
2) load management.

In the first place, improvement of the energy efficiency implies performing the same type of operations for less energy. These actions consider reduction of the energy use through implementation of energy efficient equipment (such as energy saving lighting devices, more efficient air conditioning units, circulation pumps etc) and they are focused to reduce the energy consumption and indirectly to reduce the peak demand. On the other hand, DSM can be achieved through the load management which this paper is focused on.

Load management [1] includes all the measures intentionally undertaken with the aim to influence the energy consumption/load profile in such a way to alter (usually to reduce) the peak demand or total energy consumption over a certain period of time. In other words, it includes redistribution of energy demand in order to spread the energy consumption evenly throughout the given period (on a daily or seasonal basis). It is directly focused on reduction of the peak demand and may or may not result in decrease of total energy consumption. Therefore, it could be stated that load management considers any reactive or preventive intentional modification of the energy consumption pattern with the aim to influence the timing, level of instantaneous demand or total energy consumption [11]. It can be achieved by applying various actions of controlling, curtailing or shifting the load. In other words, desired load shape influence can be achieved depending on the applied load management mechanism.

Apart from the load management related actions, DSM includes all the measures undertaken by the end consumer and/or utility in order to consume the energy more efficiently and subsequently to reduce the cost of the consumed power. Looking from the broader perspective, the DSM measures can also consider providing the additional power supply such as by implementation of the RES elements based on which the load demand could be met along with the reduced cost of the energy consumption.

From the perspective of the DSM application, it is important first to identify and appropriately categorise the type of the end-use load. The end-use load (electricity, heating and cooling load) could be driven by the various building systems, such as air conditioning system, lighting system or any other piece of equipment installed at the site. With respect to the mentioned, the load can be categorised according to the following [11]:

- critical load – should not be influenced (typically power supply of fundamental operation),
- curtailable load – could be reduced (the temperature set-point of the air conditioning system could be lowered during periods of high electricity price or if contracted peak consumption is being approached),
- reschedulable load – could be shifted (forwards or backwards) in time (pre-cooling of a building can be performed early in the morning before there is an actual cooling demand).

Having in mind the above listed categories, identification of the curtailable and reschedulable load is a prerequisite in order to select and apply suitable DSM measure.

III. Proposed GA Based Approach

The objective of this paper is to propose the corresponding DSM related measures to the facility/energy manager by taking into account the forecasted energy load profile of the building and applied tariff scheme per energy carrier (such as electrical energy, natural gas, fossil fuel etc). The proposed solution is based on the GA [2] which is used in order to discover the optimal energy load profile over a given time window. GA optimization was chosen as one of the powerful search heuristics inspired by the process of natural evolution (such as inheritance, mutation, selection, and crossover) and which is often used for search problems and optimization tasks. As such, the GA was taken as the main paradigm of the proposed solution, facilitating search for the optimal load distribution which should be followed through the corresponding DSM related measures.

The proposed solution supports single, as well as multiple loads optimization which considers redistribution of demanded energy per load (such as per electricity load, heating/cooling load). Moreover, one time step, as well as multiple time steps optimization is supported, depending on the time span of the given window interval, i.e. period of time within which DSM optimization should be performed. As it was mentioned, the main idea of the load management performed by GA optimization procedure is to redistribute the energy demand in such a way that the lowest possible cost of demanded energy is achieved under certain constraints. This task can be tackled through various methods of curtailing or shifting the load, among which the load shifting was incorporated by the GA optimization in order to avoid the peak hours as well as reallocation of the load by taking into account the applied tariff scheme (to avoid high tariff intervals).

A. Optimization Objectives and Constraints

The GA optimization process was performed within a multidimensional space defined by the given constraints, such as the allowed energy consumption deviation from the forecasted one, so called energy consumption margins, which define maximal and minimal energy consumption bounds. This constraint was taken into account to prevent significant disturbance of the regular end-user operations, which are not usually very flexible. On the other hand, the greater the deviation from the forecasted/regular energy consumption profile is defined (by introducing the more flexibility in end-user operation), the larger the space for the optimization algorithm will be, which consequently could yield better overall result. Furthermore, one of the objectives of the GA optimization process was to preserve the total energy consumption per load. The assumption was made that the consumer operations, looking from the perspective of the total demanded energy, should not be significantly altered (reduced or decreased in a given time window), but only redistributed. In other words, these actions only suggest reallocation of the end-user operation, but not their cancellation.

Additionally, one of the frequently applied load management measures, the load shifting, was taken into account, which is aimed to reduce the peak consumption and reallocate it to the off-peak periods in the given time window. The load shifting was applied through the definition of the maximal allowed energy consumption, which can be implemented per corresponding load for the desired time step or throughout the time span of the given window interval. In order to discover and propose the optimal energy demand profile (from the financial perspective for instance) to the end user for the given use-case scenario described in Section IV, all of the previously mentioned constraints and DSM measures were applied in combination.

B. GA Optimization Parameters

The aim of the GA optimization process was to find the optimal “individual” within a search space defined by the given (i.e. forecasted) energy load profile and corresponding constraints (such as energy consumption margins, maximal peak energy consumption, total demanded energy preservation). GA optimization for the purpose of this paper was performed over the population of 100 “individuals”. The population size was chosen as such having in mind that large population enables more thorough search for the optimal solution (possible discovering a global minimum and avoiding the local minimum), but causes the algorithm to run more slowly. The “individual” in this context considers a set of values (per one or multiple loads) indicating consumed energy per corresponding load for one time step or over a time span of the given window interval.

The result of the GA optimization should be the optimal load profile (i.e. “individual” in GA terminology), i.e. the optimal point in multidimensional search space representing the proposed energy load distribution which yields the lowest possible cost under the applied tariff scheme. Each “individual” of the population was evaluated based on the predefined GA fitness function which calculated its cost, while taking into account the defined prices per corresponding energy carrier (as part of the given tariff scheme). In other words, the overall cost of the entire energy load profile was taken as the fitness function value, which was used to rate the “individuals” within the population. The fitness function value of the corresponding “individual” was calculated by determining the cost of the energy carriers required at the supply side to satisfy the demand side. By redistribution and reallocation of the demanded energy among different loads, i.e. by gene modification of the individual, the task of the GA was to discover the optimal load profile (“individual”) in terms of the cost of the consumed energy indicated by the fitness function.

Due to the nature of the problem, all the individuals within the population were represented as a set of positive real numbers indicating the load demand. Initial population was randomly chosen and dispersed over the search space defined by given energy load profile and margins. The number of individuals with the best fitness function values that were taken directly into the next generation, so called elite individuals, was set to 2. Number of elite individuals was set intentionally to the low value in order to avoid that the fittest individuals dominate the population, which could make the search less effective. Apart from the mentioned elite individuals, the rest of the population was considered for crossover and mutation. Crossover fraction took share of 60% of the remaining individuals, while the 40% was taken for the mutation by introducing random changes to the genes of the corresponding individuals, but by taking into account the above-mentioned bounds and constraints. In such a way, mutation provided a genetic diversity and enabled the GA to search a broader space.

Selection of the pairs of the individuals, so called parents, that were combined and used for production of new individuals of the next generation, i.e. for crossover, was performed based on their fitness function value. More precisely, the selection was performed by simulating a roulette wheel method, which assumed that selection area of the corresponding individual is proportional to the individual’s expectation, i.e. the fitness function value. The GA optimization was run for 500 generations. In order to reduce the execution time of the GA optimization process, additional stopping criteria were implemented, which terminated the optimization process if algorithm entered the stationary area. The stationary area was considered to be around the optimal point when the weighted average change in the fitness function value, i.e. the improvement of individuals was below a given threshold for defined number of generations, so called stall generation limit, or when the fitness function value of the best individual was less than defined limit.

IV. Optimization Performance and Results

In order to evaluate the performance of the proposed GA based approach to DSM, optimization process was carried out upon the use case scenario having two energy carriers at the supply side (for instance electricity and natural gas), RES generation elements and two loads at the demand side (such as electricity and heating load). For such use case scenario, a simple facility infrastructure modelled with energy conversions, as shown in Figure 1, was taken into account. Conversion from electrical energy to electricity load was modelled with efficiency of 0.99, indicating that only small part of electrical energy is lost

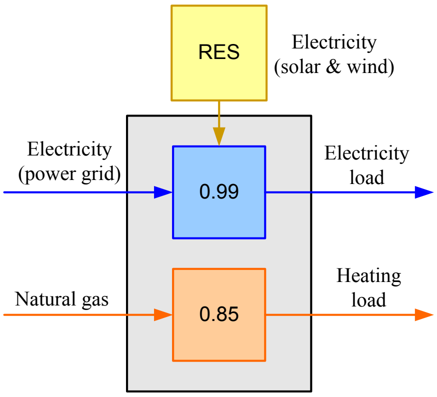

Figure 1. Use case facility infrastructure

due to the distribution. On the other hand, conversion from natural gas to supply heating demand was given with the efficiency of 0.85. Additionally, RES generation elements (solar and wind energy based) for electricity production were included as well. Corresponding load distribution of the defined facility infrastructure indicating the forecasted energy consumption for the time interval 06-17h (with one hour resolution) was given as shown in Figure 2. In addition, dynamic tariff scheme was taken into the consideration applied per electrical energy, while in the case of natural gas the fixed price scheme was applied as it can be seen in Figure 3. Distribution of RES generated energy (from photovoltaics and wind turbines) is presented in Figure 4.

Previously described setup of the GA optimization process was performed upon the defined use case scenario. The task was to apply the DSM measures upon the forecasted load profile for a given time interval 06-17h, for two loads (in this case for the electricity and heating load) as shown in Figure 5. Based on the load profile, the search space for the GA was defined by energy consumption margins, which, in this scenario, were set to 3p.u. (per unit of energy) for both loads (as indicated by the blue bars in Figure 5). Energy consumption margins

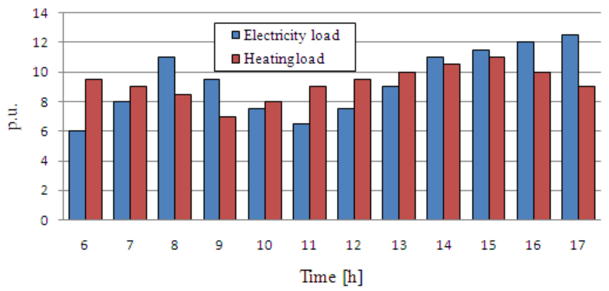

Figure 2. Load distribution

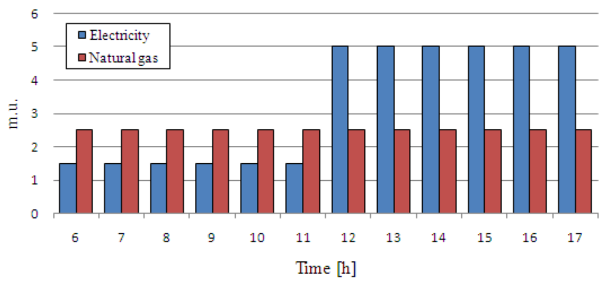

Figure 3. Applied tariff schemes

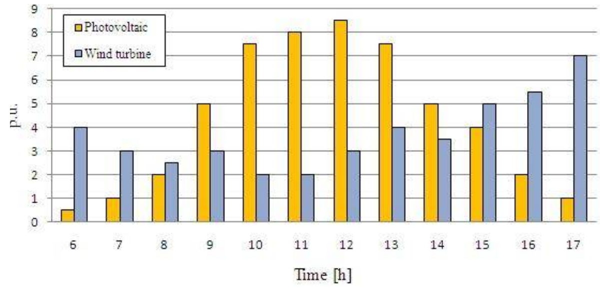

Figure 4. Renewable energy sources

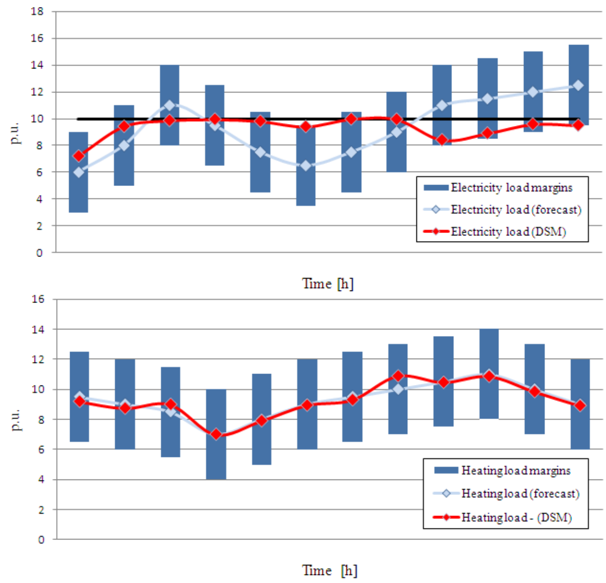

Figure 5. Load distribution before and after applied DSM

were intentionally chosen to be relatively small in order to avoid significant disturbance of the regular end user operations.

Additionally, in order to tackle the peak energy consumption instances, maximal allowed energy consumption was set to 10p.u., but only for electrical energy. Based on the given load distribution it can be noticed that consumption exceeded in certain time intervals the allowed threshold (as presented in Figure 5). As it was previously mentioned, additional constraint was applied, related to the preservation of the total demanded energy per load as compared to the forecasted load distribution. For the purpose of this scenario, the fitness function was calculated by taking into account the tariff scheme per energy carrier as illustrated in Figure 3. It is important to emphasize that the applied tariff scheme indicated the price distribution per corresponding energy carrier at the supply side (in this case electricity and natural gas) over a given time period.

The progress of the GA optimization process, i.e. the evolution of the best and mean fitness function value (calculated upon the entire population) over the 500 generations is presented in Figure 6. Based on the presented results, it can be concluded that GA optimization reached its optimal solution around 350th generation, while further evolution of the population did not show any significant improvements.

By performing the GA optimization process upon the given load profile, under the mentioned constraints and DSM measures, the resulting load distribution is presented

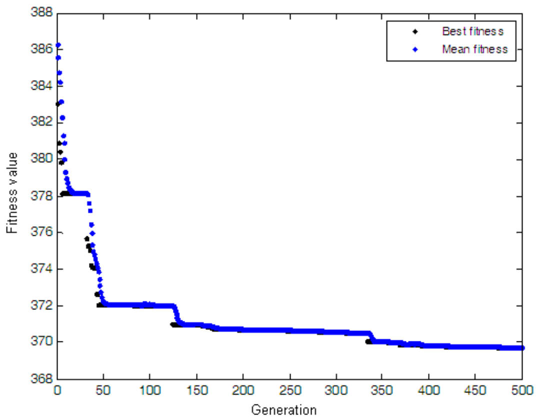

Figure 6. GA optimization process (best and mean fitness value evolution)

in Figure 5. As it can be noticed, the GA successfully managed to alter the given load distribution in order to comply with the defined constrains revealing the optimal load profile with the lowest cost under the applied tariff scheme. For instance, the peak electricity consumption at 08h and energy consumption above maximal allowed limit from 14h were successfully curtailed. Electricity load from the evening hours was shifted to the period 12-14h due to the increased RES generated energy and to the morning hours having in mind the lower electricity cost. On the other hand, heating demand remained almost the same since the fixed price scheme was applied for natural gas with no additional constraints. The cost of the proposed load distribution (end-use load profile discovered by the GA) was 369.72m.u. (in abstract monetary units), while the cost of the initial forecasted load distribution was 419.61m.u. as shown in Table I. In other words, the proposed approach made cost savings of 11.89% comparing to the baseline (without DSM applied). It is important also to emphasize that savings which could be achieved by the proposed approach are specific to the analyzed use case scenario (i.e. facility infrastructure, applied tariff scheme, constraints etc).

TABLE I
COMPARISON RESULTS

Approach	Cost [m.u.]	Savings [%]
Without DSM (baseline)	419.61	0.00
With GA based DSM applied	369.72	11.89

V. CONCLUSIONS

Both industrial and residential domains are forced today by stringent energy supply constraints to take into account the potential benefits of introducing DSM measures. One of the goals of performing the DSM measures is to lower the energy supply and distribution requirements, but at the same time to answer the needs of much higher number of end-users with the same energy supply/distribution capacity. Various optimization paradigms were utilized so far to apply resource and load management. One of the most popular approaches is based on the GA paradigm. In this paper, a generic GA based approach to DSM was proposed and analyzed. GA paradigm was chosen as suitable to solve the problem of discovering an optimal end-use load distribution and applying adequate DSM measures. Depending on the use case scenario and facility infrastructure of interest, both single as well as multiple loads optimization is supported. In addition, proposed approach supports the optimization of given loads within one time step, but also over the predefined time interval.

The proposed solution includes the application of various DSM measures such as curtailing or shifting the load, implemented solely or in combination, which depends on a way the optimization constraints are defined. In that manner, it is possible to reallocate the load from the peak hours or from the high tariff periods. The degree of influence of applied DSM measures on the end-user operation could be varied depending on the type of the load (critical or non-critical load). Preservation of total energy consumption per load was also taken into account by the proposed approach.

For evaluation of the proposed solution and its performance, a simple use case scenario of two energy carriers, RES generation elements and two loads was considered. More precisely, the GA optimization procedure was carried out upon the given forecasted load profile and applied tariff scheme. Additional constraints were defined representing the energy consumption margins and maximal allowed consumption. By analyzing the optimization results it was concluded that the proposed solution gave substantial improvements in terms of cost savings as compared to the forecasted energy load profile taken as a baseline.

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