A Genetic Optimization Technique for the Strategic Use of Renewable Energy Supply

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Abstract. This paper presents a new strategy to solve the optimal constrained problem of scheduling the work phases of households. In particular, the real-world application refers to a new generation of appliances having advanced communications and networking features and fed by an opportune system chasing the curve of availability of locally produced renewable energy. The proposed work allows appliances to adapt their operations to the current state by activating low power mode and waiting for the right time to start a cycle with high consumption, for example, when the system delivers more power. The goal is to find a solution to make these houses energy self-sufficient, allowing the use only when there is availability. The constrained optimization is solved by the well known Genocop III, proposed by Michalewicz [1]. The results of the experimental implemented solution reveal good performance and accuracy and are presented, at the end of this paper, by means of a prototype of a graphical interface that shows the expected trend of generated power, the consumption power trend of scheduled activities and the expected consumption power trend of households.

Keywords: households, renewable energy sources, constrained optimization problem, scheduling.

Introduction

The objective of this work is the study and modeling of a smart home automation environment to optimize the use of energy resources, achieve greater savings in economic terms, to ensure better integration of renewable energy sources (RES) to ensure high energy efficiency and allow a rational management of loads characterized by significant absorption of power. Renewable energy is energy which comes from natural resources such as sunlight, wind, rain, tides, and geothermal heat, which are renewable (naturally replenished). Renewable energy replaces conventional fuels in four distinct areas: electricity generation, hot water /space heating, motor fuels, and rural (off-grid) energy services [2].

Mainstream forms of renewable energy are:

- Wind power: wind power plants make use of wind to generate electricity. Their operation is due to the presence of wind turbines, which are appointed to convert the kinetic energy of wind into mechanical energy, then it is converted into electrical energy.
- Hydropower: energy in water can be harnessed and used. Since water is about 800 times denser than air, even a slow flowing stream of water, or moderate sea swell, can yield considerable amounts of energy.
- Solar energy: energy derived from the sun through the form of solar radiation. Solar powered electrical generation relies on photovoltaic and heat engines. A partial list of other solar applications includes space heating and cooling through solar architecture, day lighting, solar hot water, solar cooking, and high temperature process heat for industrial purposes.
- Biomass: Biomass (plant material) is a renewable energy source because the energy it contains comes from the sun. Through the process of photosynthesis, plants capture the sun's energy. When the plants are burnt, they release the sun's energy they contain. In this way, biomass functions as a sort of natural battery for storing solar energy. As long as biomass is produced sustainably, with only as much used as is grown, the battery will last indefinitely.
- Geothermal energy: energy obtained by trapping the heat of the earth itself, both from kilometers deep into the Earth's crust in volcanically active locations of the globe or from shallow depths, as in geothermal heat pumps in most locations of the planet.

This research is motivated by an European Directive 2009/28/EC, which would serve to promote the use of energy produced from renewable sources. With regard to the Italian law, about the photovoltaic systems there is a "Fourth Energy Count" that makes reference to the Italian Minister Law of 05/05/2011. This law also regulates the remuneration of the produced energy and injected into the network by providing two mode:

- Withdrawal dedicated: in addition to the sale on the open market and selling at prices guaranteed minimum, is given the opportunity to sell the energy produced in a simplified manner, but at market price. A key aspect to note is the return on an hourly basis, which rewards the PV production that occurs mainly in the time paid more.
- Exchange on site: This mechanism allows you to enter the generated electricity that is not immediately self-consumed in the network, and then pick it up at a later time to meet their energy needs. Its main characteristic is freeing the user from using energy produced by photovoltaic exclusively when it is produced. The user stays connected to the electricity grid, the energy is consumed when it is needed.

Some work have already been reported by several researchers that use genetic algorithms, neural networks, dynamic programming and fuzzy logic as methods to solve the complex nonlinear problem of building energy system optimization [3].

Many articles show that genetic algorithms are useful in environmental issues and scheduling in general [4,5,6,7,8]. Predictive control is widely adopted to optimize building behavior to save energy and improve comfort. The future load and environment are input into a building simulation model, an optimization algorithm is used to find optimum set points [9,10,11,12]. Compared to other systems, this paper proposes a system that directly schedule user activities according to energy availability and knowledge of his habits (which are foreseen). The developed system promotes self-sufficiency of the house trying to consume the energy produced on site. This leads to cost savings, discouraging the purchase of energy from suppliers. To achieve this it is necessary to schedule the activities respecting the time and power constraints.

Description of the real-world environment

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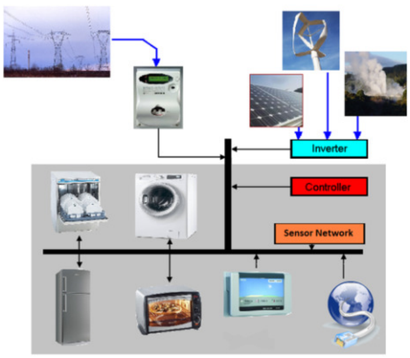

Fig. 1. Environment

Fig.1 showed the environment to manage in outline diagram. The house network is mainly composed of a communication bus through which the various appliances schedulable are to be able to communicate with the centralized controller. In addition, a network of sensors distributed appropriately allows the controller to continuously supervise the environment. The operator station is designed in order to use data from the web and information about the production of energy from renewable energy sources (e.g. photovoltaic and mini-wind).

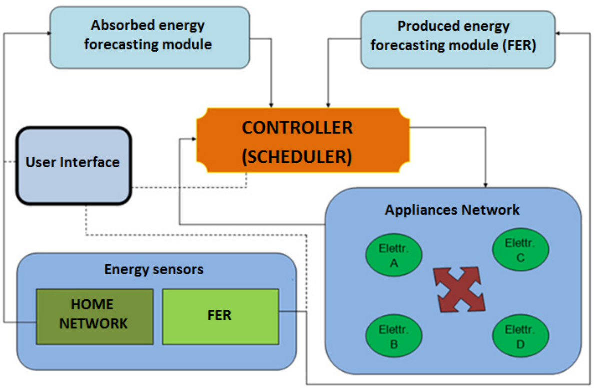

Fig. 2. Architecture

Figure 2 shows a detailed diagram of the system. In this scheme six logic modules cooperating with each other are identified :

- The central controller, in which the logic of scheduling resides ;
- The network appliance, via a data bus is to be able to send their requests to the controller;
- The predictor modules, for prediction of two power curves throughout the day energy production from renewable energy sources and the expected energy use;
- The sensor network, in order to support the predictor modules;
- The user graphical interface, for monitoring the solution of the controller.

In the network appliances there are appliances that have a machine cycles (e.g., washing machine, dishwasher or dryer). In particular it refers to a new gamma of appliances able to send to the controller a packet of information about the program the user wants to launch. Each program will be divided into phases that follow each over time, each of which may be preceded by a waiting period. So, for each phase, it has to specify duration, the maximum power absorbed and the maximum waiting time from the end of the previous phase. The user must specify the deadline: that the time within which wants the program to be completed.

These values are stored and / or calculated (estimated) at the time of the appliance's request according to current conditions, for example a washing machine can dynamically update all fields of consumption and duration of the phases based on the weight of the laundry or the degree of dirt. The produced energy forecasting module is of the schedule. In a database there are stored information about on the site of the system (e.g., latitude and longitude) and information about the renewable energy systems (e.g., rated power). In this way the system can come up with a curve in the optimal environmental conditions. This module should also provide the weather forecast calculation unit acquired through a web server that communicates such speed and wind direction (for small wind turbines) and the level of cloud cover (for PV), for example every hour. The checker validates the correctness of the forecast through the real value of power generated from renewable sources. If the instantaneous real power differs from the prediction of a certain threshold, an event will correct so the entire forecast. Through the absorbed energy forecasting module the system is able to predict the user's consumption during the day . The predictions are based on historical data stored in a dedicated database. The checker block monitors the value acquired by the sensor network, and if this value differs significantly from the expected, the curve will be updated accordingly. The controller is the heart of the system, within which lies the control e the schedule logic (based on the genetic algorithm Genocop III). The controller is able to accept requests from programs of the various appliances. The requests are then collected in buffer, processed and given in input to the scheduler. After execution, the scheduler generates the timeline in which the phases of each program will succeed. The schedule must take into account: the prediction of power from renewable energy, the forecast of consumption, the price of purchase and sale of energy in different bands (available in the world wide web). It is also important to say that the scheduling algorithm was also launched following the occurrence of two events set out above a prediction error.

Description of the problem and of its solution's strategy

The first step to solve the problem was trying to explore the entire solution space by an exhaustive algorithm. As expected, with the increase of the number of variables, the computation time grew with a factorial dependence by n (O(n!), where n is the number of variables).

The problem considered is regarded as a constrained optimization problem and then its solution is implemented by means of the well known Genocop III algorithm. Genocop (GEnetic algorithm for Numerical Optimization of COnstrained Problems) assumes to solve an optimization problem handling only linear constraints and uses a feasible starting point or feasible population preserved during the evolutions by means of several operators designed to perform this task.

Genocop III incorporates the original Genocop system, but also extends it by maintaining two separate populations, where a development in one population influences evaluations of individuals in the other population. The first population consists of so-called search points from S, which satisfies linear constraints of the problem (as in the original Genocop system). The feasibility (in the sense of linear constraints) of these points is maintained, as before, by specialized operators. The second population consists of so-called reference points from F; these points are fully feasible, i.e., they satisfy all constraints. Reference points R, being feasible, are evaluated directly by the objective function (i.e., eval(R) = f(R)). On the other hand, infeasible search points are "repaired" for evaluation and the repair process works as follows. Assume, there is a search point S, not fully feasible. In such a case the system selects R, one of the reference points (better individuals have better chances to be selected), and creates random points T from a segment between S and R by generating random numbers from the range [0;1]: T = a S + (1 – a) R . Once a feasible T is found, eval(S) = eval(T) = f(T). Additionally, if f(T) is better than f(R), then the point T replaces R as a new reference point. Also, T replaces S with some probability of replacement p_r. The Genocop III avoids many disadvantages of other systems. It introduces few additional parameters (the population size of reference points, probability of replacement) only. It always returns a feasible solution. Making references from the search points searches a feasible search space F. The neighborhoods of better reference points are explored more often. Some reference points are moved into the population of search points, where they undergo transformation by specialized operators (which preserve linear constraints) [1]. In order to consume only energy available from renewable energy sources, or to maximize its use, we schedule domestic activities or their atomic steps by controlling their start time and managing the waiting times between the various phases of those activities, taking into account, at the same time, the specifics set by the user in terms of deadlines and the threshold fixed by the electricity provider in terms of maximum guaranteed power. With these specific on mind, the solution of this scenario suggests to encode the genetic algorithm chromosome with a number of genes equal to the total number of phases of all activities. Then, each gene represents the delay between the considered phase and the previous one where in the case of first phase of an activity indicates the delay between receipt time of the request by the system and the start time of the first phase.

Each task to be executed, contains information about its phases, namely its duration d_i , power consumption p_i and the maximum delay with its previous phase $tmax_i$. Defined the chromosome, the constraints of the problem are explained in the following formulas divided in three different kinds:

Physical constraints due to the maximum delay between two phases:

$$x_{i,j} \le tmax_{i,j}, \forall i, j \wedge i \ne 1 \qquad \textbf{(1)}$$

where $x_{i,j}$ is the delay between the (i-1)th phase and the (i)th phase of the (j)th activity.

Physical constraints due to the power consumption:

$$\sum_{j=1}^{n} p_j\left(t\right) \le Pmax(t), \forall t \qquad \textbf{(2)}$$

where $p_j(t)$ is the power consumption of each appliance at time t (n appliances in total), while Pmax(t) is the maximum available power at the same time.

Additional constraint to respect the deadline set by the user:

$$O + \sum_{i=1}^{m_j} (x_{i,j} + d_{i,j}) \leq D_j, \forall j \quad \textbf{(3)}$$

where O is the system time, i.e. when a new request is generated, x_i is the delay between the $(i)^{th}$ stage and the previous one, d_i is the length of the $(i)^{th}$ phase and D_j is the deadline of the $(j)^{th}$ activity. Formalized the problem, each linear inequality that is summarized above, is made explicit at run-time each time a task needs to be done. It has dynamically built an input file for Genocop III which provides the best schedule that has to respect these constraints and agree with the fitness function evaluated according to the following features:

- Optimal use of Energy produced from RES;
- Real cost of Energy;
- Reliability of weather forecasting;
- The need to terminate the task as soon as possible

The provided genetic algorithm solution meets all the constraints and the four aspects listed above. Some test results are shown in Tab.4 and Figure 4.

Experimental Results achieved by the implemented tool

The work already described has been implemented by means of a simulation software. Since a testing environment does not exist, this software has been the only way to validate the study that has been done, giving encouraging results .

The software allows to simulate the home environment and it offers a possibility to the user of enter the utilities that will be scheduled throughout the day. In that way, the interface enable to specify the time of the request and the deadline for when the task will be completed. This insertion of time by the user allows us to simulate the normal flow and turnover time of the events that occur during the day. Each program has associated data, that will be communicated from the device, such as an ID of appliance, names and number of programs, the duration and power of the phases and the maximum delay between two phases. This data, combined with the deadline and time of the request allows us to run the algorithm Genocop III. On the basis of the available power, it will return the chromosome representing the suboptimal scheduling, specifying for each program the delay for each phase. The software needs to know, from the day of simulation, more useful data such as:

- The curve of expected use: historical data allow us to predict consumption of not schedulable utilities;
- Total production of renewable energy: obtained on the basis of installation data;
- Time slots and prices: the real energy cost is computed taking into account the various bill components.

In addition to the launch of new applications, the software allows you to simulate two events that in real system will be launched automatically by a dedicated controller. This two are: the production prediction error and consumption prediction error. Collected all necessary data, each event causes a scheduling algorithm call based on the power curves and phase appliances not yet performed. Computational complexity depends on various factors, such as: deadline, the cost of purchase and sale of energy, the actual availability of energy, the excess of the maximum power absorbed, the reliability of weather forecasting to calculate renewable available power . Suppose to launch at 08:00 two different programs with the following specifications:

Table 1. Scheduling specification, where for the first phase the maximum waiting will be automatically set by total duration and deadline and then is fixed -1

		Phases		
Household appliance	Program	Power (KW)	duration	Maximum waiting
Washing machine	Very Dirty Cloths	0.05	12	-1
		2	14	6
		0.06	8	6
		1	10	6
		0.05	10	6
		1.05	6	6
Dish washer	Very Dirty Dishes	2	20	-1
		1	20	6
		0.06	10	6
		1.05	16	6

Before launching the scheduling, the application defines the input file for Genocop III; setting the deadline for both programs at 12:30 and assuming a discrete step of 2, we have that:

- The number of variables is 10 (schedulable delays);
- The number of domain constraints is 10 (equal to the number of variables);
- The number of linear inequalities is 2 (equal to the number of programs);
- Domain limits for initial delay is :
  - 105 time units for first program;
  - 102 time units for second program;

  These two calculated values are, in this case, also known term of the inequality linear.

The result of the schedule with a summary of the parameters and constraints is shown in the output file. Of particular interest are therefore the values of the evaluation function assumed run-time, and the best individual found:

Table 2. Evaluation function result

Evaluation Count	1447
Best Ref. Value	-24.6058

Table 3. Scheduling solution. Delays of the activities

$x_{1,1}$	69
$x_{2,1}$	1
$x_{3,1}$	0
$x_{4,1}$	0
$x_{5,1}$	0
$x_{6,1}$	0
$x_{1,2}$	56
$x_{2,2}$	0
$x_{3,2}$	1
$x_{4,2}$	1

In this case, then the washing machine will operate between 10:18 and 11:20 because a delay of one time unit has been generated between the first and second phase; the dishwasher will turn 56 time units after its launch and will end at 11:02 with a delay of one unit between second - third phase and third -fourth phase.

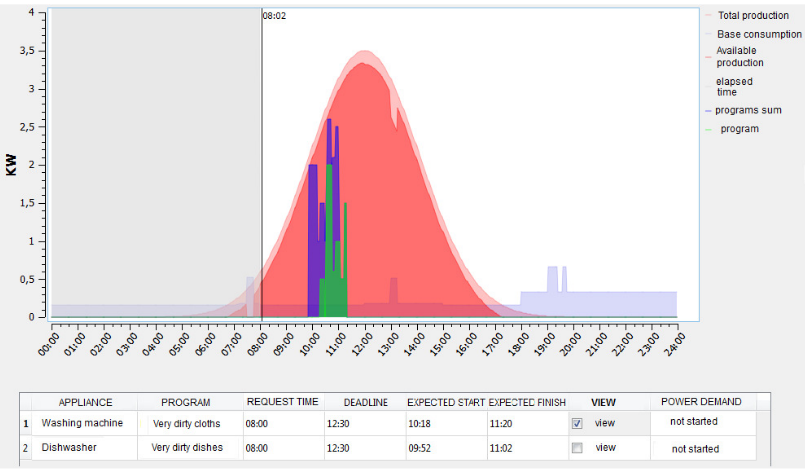

Fig. 3. A scheduling example result.

Table 4. Scheduling solution. Expected Start and Finish Time

Appliance	Program	Request Time	Deadline	Expected Start Time	Expected Finish Time
Washing machine	Very dirty cloths	08:00	12:30	10:18	11:20
Dishwasher	Very dirty dishes	08:00	12:30	09:52	11:02

In this example it is possible to see that scheduling does not require a purchase from energy provider.

To analyze the resources required by computation, it is done a scheduling of high computational difficulty. It's supposed to launch at 10:00 a.m. the following requests:

Table 5. Scheduling solution. Delays of the activities

Program	Number of phases	Average absorption (kW)	Peak of absorption power (kW)	Total time (min.)
#1	6	1.01	2	60
#2	6	1.01	2	60
#3	4	1.28	2	66
#4	5	1.46	2.2	70

In this case the difficulty of scheduling is not only given by the number of chromosome's genes (15 bound variables) but also by the particularly stringent deadline. For this processing, the algorithm needed, on a 10 trials average, of 370 ms (with large variability of time) and a peak of memory employment equal to 16844KB; just reported data refer to an Intel Core en-2630QM, 2.0GHz with 4GB of RAM. These average time is the computation time of the complete application including a GUI; therefore just reported resources are widely over estimated.

Below is analyzed the variability of the solutions which the algorithm converges. The table shows the results of scheduling for a single six-phase program launched at 00:00 with deadline at 22:00.

Table 6. Scheduling solutions

	Genes						Fitness function	Start time
#1	460	30	0	0	0	0	-103.27	08:22
#2	473	17	0	0	0	0	-103.25	08:22
#3	479	10	0	0	0	0	-103.22	08:21
#4	468	23	0	0	0	0	-103.26	08:23
#5	460	30	0	0	0	0	-103.27	08:22
#6	460	30	0	0	0	0	-103.27	08:22
#7	469	22	0	0	0	0	-103.26	08:23
#8	460	30	0	0	0	0	-103.27	08:22
#9	470	21	0	0	0	0	-103.26	08:23
#10	476	15	0	0	0	0	-103.23	08:23

Table 7. Mean and variation of Scheduling solutions

Mean	467.5	22.8	0	0	0	0	-103.26
Standard deviation	6.8	6.9	0	0	0	0	-0.0173

Despite the vastness of the possible solutions it can be noted that the variability of the values to whom the algorithm converges is really reduced and that the variability in the first two delays depends on the shape of the available energy curve

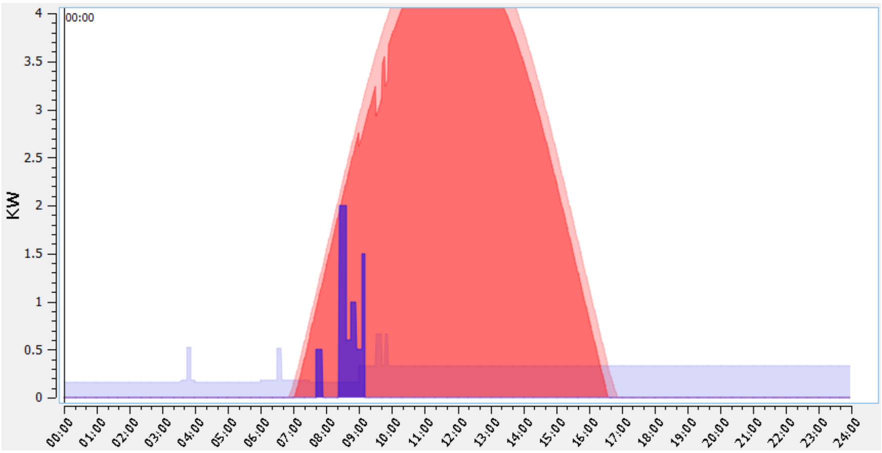

Fig. 4. A scheduling result.

The position of the first phase is variable, but it is always below the power production curve. Of great interest is the coincidence of the start of the second phase in all tests, after which the delays are always zero.

Conclusions

This paper stated as the synergy between advanced programming techniques, such as genetic algorithms, and use of sources on-site renewable energy, will produce significant energy savings with obvious positive impact on economic and environmental. In particular, the home system has been analyzed and schematized (see Fig.1 and Fig.2), it has been studied the behavior of appliances energy. These are represented as a succession of phases with different power consumption and duration. To save energy and consume only one produced from renewable energy sources it has been designed a system that is able to predict the power output curve, the curve of power consumption by users and then schedule the tasks required so that you do not purchase energy from the supplier. Being a scheduling constrained optimization problem, it was solved by using Genocop III, then the chromosome was appropriately designed to encode as solution the list of activities to be performed and their start and end times of activity (which must respect the deadline set by user). The use of genetic algorithms, was an essential aid as well as a powerful tool for quick search of the excellent solution. As discussed and shown in the previous paragraph, the genetic algorithm found in a very short time (few seconds) the optimal solution or sub-optimal allowing the system to implement the decision almost at run time (in the example 2 minutes delayed). The experimental system is designed for insertion of the request at run time calculating every time the constraints of time and power and show good performance in several real tests.

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