DISTRIBUTED GENETIC ALGORITHMS SYSTEM FOR EFFICIENT USE OF ELECTRICAL ENERGY

F.Garzia, G.M.Veca
Dipartimento di Ingegneria Elettrica
Università degli Studi di Roma "La Sapienza"
Via Eudossiana, 18, 00184 Roma, Italy

INTRODUCTION

Evolutionary strategies such as the one offered by the genetic algorithms have demonstrated to be very efficient in the correct use of energy.
They can be applied using simple electronic microcontrollers that read input data such as the presence of people inside the room, the outside temperature, the inside temperature, the time, the date and other data that are useful to characterise the desired application and so on. The output data are represented by the desired electrical efficient use of energy as a function of the input data that act directly on the electrical and the air conditioner installations[1-5].
This kind of application ensures a local efficient use of energy but its not capable of operating from a more general point of view that is to ensure an efficient use of energy in an extended number of rooms or in a building, given a certain power delivery amount that can not be overcame.
The proposed system is composed by a series of local genetic controllers (LGC) that learn and adapt their energy management strategy according to the variations of input data, ensuring a local efficient use of energy and a perfect comfort of the rooms occupants, switching and trimmering properly all the electrical loads. Using their evolutionary features, the local controllers are capable of developing proper forecasts of energy needs of the controlled room, that varies constantly as a function of the variations of the input data.
The local controllers are connected through a communication bus to a central genetic controller (CGC) that continuously receive the programmed energy forecasts of the local controllers. The central controller evaluates simultaneously all the energy forecasts of the local controllers, together with their relative priorities and assigns them a certain electrical power quota, that can respect their requests or can be below their requests, according to the global situation of electrical energy needs: if the request is respected the local controller actuates the programmed energy forecast to ensure an optimal comfort of the room occupants, otherwise the local controller disconnects the electrical loads characterized by a reduced priority.
During the normal working the local controllers evaluate continuously the power need forecasts and as soon as there is a discrepancy between the effective needs and the forecasted needs, in term of increases or decreases, they immediately communicate these variations to the central controller that reallocates these energy variations to the other controllers, always ensuring an optimal energy management and a respect of the maximum delivered power.
The purpose of this paper is to illustrate the capability of this system characterized by an extremely dynamic behaviour that adapts continuously to the electrical power needs of the controlled building, ensuring always the best comfort of the occupants, reducing energy wastes and never overcoming a fixed delivered power.

GENETIC ALGORITHMS AND CLASSIFIER

Genetic algorithms (GAs) represent wide range numerical optimisation methods, that use the natural processes of evolution and genetic recombination.
They can be used in different application fields, thanks to their versatility.
GAs are very useful when the target is to find an approximate global minimum in a high-dimension, multi-modal function domain, in a near-optimal manner.
They can easily handle discontinuous and non-differentiable functions, on the contrary of the most optimisation methods.

The GAs encode each parameters of the problem that must be optimised into a proper sequence (where the alphabet used is generally binary) called a gene, and combine the different genes to constitute a chromosome. A proper group of chromosomes, called population, experience a Darwinian processes of natural selection, mating and mutation, creating new generations, until it reaches the final optimal solution driven by a desired fitness function.
A classifier system is a machine learning system that learns syntactically simple string rules to guide its performance in an arbitrary environment. A classifier system is composed by three sub systems:
1) rules and messages system
2) apportionment of credit system
3) genetic algorithm.

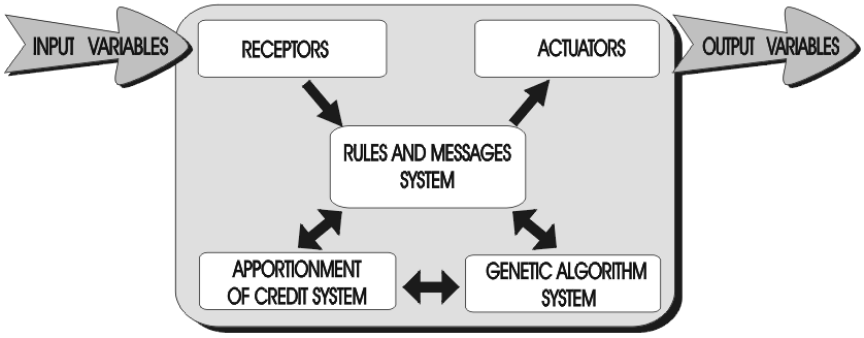

Fig.1 Scheme of a Genetic Classifier

The rule and message system of a classifier system is a special kind of production system, that is a computational scheme that uses rules as its only learning method. Although there is a wide variation in syntax between production systems, the rules are generally of the form 'if <condition> then <action>'. The meaning of a production rule is that the action may be taken when the condition is satisfied. Even if this simple device for representing knowledge can seem to be too constraining, it has been shown that production system are computationally complete and also convenient, since a single rule or a small set of rules can represent a complex set of thoughts compactly. Classifier systems restrict a rule to a fixed-length representation. This restriction has two benefits: all strings under the permissible alphabet are syntactically meaningful and fixed string representation permits string operators of the genetic kind, letting possible a genetic algorithm search of permissible rules.
Classifier system use parallel activation whereas traditional expert systems use serial rule activation. During each matching cycle, a traditional expert system activates a single rule. This rule-by-rule procedure is a bottleneck to increase productivity, and much of the difference between competing expert system architectures concerns the selection of the better single rule activation strategies for this or that type of problem. Classifier systems overcome this bottleneck, allowing parallel activation of rules during a given matching cycle. Thanks to this feature, classifier systems allow multiple activities to be coordinated simultaneously.
When choices must be made between mutually exclusive environmental actions or when the size of the matched rule set must be pruned to accommodate the fixed length message list, these choices are postponed to the last possible moment, and the arbitration is then performed competitively.
In traditional expert systems, the value or rating of rule relative to the other rules is fixed by the programmer in conjunction with the expert group of experts being emulated. In a rule learning system, the relative value of different rules is one of the key pieces of information that must be learned. To facilitate this kind of learning, classifier systems force classifier to coexist in an information-based service economy. A competition is held between classifiers where the right to answer relevant messages goes to the highest bidders, with the subsequent payment of bids serving as a source of income to previously successful message senders. In this way a chain of rules is formed from the input of the system, represented by the detectors, to the output of the system,

represented by the actuators. The competitive nature of the economy ensures that good rules, that are the more profitable, survive and bad rules, that are unprofitable, die off.
The apportionment of credit is very important in a classifier system. It uses a sort of internal currency that is exchanged and accumulated to provide a natural figure of merit. Using a classifier's bank balance as a fitness function, classifier may be reproduced, crossed, and mutated, according to the criteria illustrated in the previous paragraphs. Thus, not only can the system learn by ranking extant rules, but it can also discover new possibly better rules as innovative combinations of its old rules.

DESCRIPTION OF THE DISTRIBUTED GENETIC SYSTEM

We already said that the system is composed by a series of local genetic controllers (LGC) that manage locally the electrical loads and prepare energy forecasts that are constantly sent to the central genetic controller (CGC).
The LGC is composed by an electronic microcontroller that controls one or more than one room. It is equipped with a certain number of input sensors and a certain number of output actuators, which manage the electric loads and the other energy sources. The input can be represented, for example, by the presence of people inside a room, the outside temperature, the inside temperature, the time, the date and other data that are useful to characterise the desired application and so on. The output data are represented by the desired energy management strategies as a function of the input data that act directly on the electrical and the air conditioner installations. The LGCs have already been studied [1-4] and their working schemes and their functionalities are not repeated here for brevity.
The CGC, whose study represents the purpose of this paper, is composed by a computerized workstation, that can be, for example, a personal computer whose nowadays computation power has demonstrated to be sufficient for our purpose. The CGC receives the power need forecasts from the LGCs and continuously reallocates eventual power variation request to the controllers, trying to ensure by a continuous training an optimal energy management and a respect of the maximum delivered power. The scheme of the system is shown in fig.2.

Fig.2 Scheme of the distributed genetic system.

It is now important to define the format of the inputs of the CGC that are the outputs of the LGCs, and the format of the outputs of the CGC that are the inputs of the LGCs.
First of all the electrical loads are supposed to be divided into two groups: the electrical loads with a high priority that are the loads that cannot be disconnected and the loads with a low priority that are the one that can be disconnected without compromising any activity. The total delivered power is also supposed to be equal to the sum of the power of the high priority loads so that, in case of simultaneous switching of all of them, their functioning is ensured. On the contrary, when there are not all switched on, a part of the power can be diverted towards the low priority loads, according to the needs expressed by the LGC, trying to satisfy, at the better level, their requests.
It is now necessary to define the minimum time interval of the power request: a good compromise between precision and volume of generated data has demonstrated to be 10 minutes, that is the LGC generates their power forecast every 10 minutes and receive instructions for power allocation from the CGC every ten minutes.
It is also necessary to choose the temporal length of the power forecast needs: a good time interval has demonstrated to be 24 hours. This means that every 10 minutes the LGCs generate 2 string messages, one for the high priority loads and one for the low priority loads, that are the output messages directed to the CGC, composed by 144 numbers (6 numbers each hour multiplied for 24 hours) indicating the power needs for the next 24 hours following the messages production.

Since it is preferred to use a binary alphabet to codify the data and obtain the best performance by the GAs [5] it has been supposed, without loss of generality, that each LGC manages no more than 2,5 kW of power with a resolution of 10 W, that corresponds to the use of 8 bits (256 numbers).
Each output strings is therefore composed by 1152 bits (144 x 8 bits=144 bytes), that is a very compact message in term of data transmission and memory occupation.
If N_{LGC} is the number of LCG present on the controlled building, the CGC controller receive, every 10 minutes, 2 N_{LGC} input messages to be managed and satisfied in the better way.
These messages are properly inserted in a string where the first element is composed by the input messages produced by the LCG 1 for the high priority loads and low priority loads, and so on for the other messages until reaching the last LCG. This string constitutes the <condition> of the general form of the rules that is :' if <condition> then <action>'. Since the action is represented by the power programs of each LCG, the <action> is characterized by the same structure of the <condition>, and the output string is properly decomposed into sub-strings that are sent to the respective LGCs.
The CGC generates its rules respecting the condition that the sum of the electrical powers used by the LCGs following the programs sent to them by the CGC, is less or equal to the total delivered power, to avoid malfunctionings. The CGC generates also the management rules respecting the condition of trying to satisfy at the best the electrical power forecast of the LGCs.

RESULTS

The distributed genetic system has been simulated and tested in a real time modality to study its behaviour and its performance.
To better illustrates the obtained results it is necessary to define some performance parameters.
Since the LGCs try to make their power forecast basing on their generated rules by learning process and since sudden changes of the environmental conditions not experienced before by the LGCs can induce error in power forecast need, it is necessary to consider this important factor. For this reason the first parameter is the Forecast Error (FE) that is related to the error between the power forecast of LGCs and their effective power needs. Given a certain LGC, if $P_F(i)$ is the power forecast at a certain time sample i, $P_E(i)$ is the effective power need at a the same time sample i and P_{MAX} is the total maximum managed by the considered LGC, we define Forecast Error of a the considered LGC the following expression:

$$FE_{LGC} = 100 \cdot \frac{\sum_{i=1}^{144} \left| P_F(i) - P_E(i) \right|}{P_{MAX}} \qquad (1)$$

From the given definition it is evident that if FV_{LGC} is equal to 100% the power forecast needs of the next 24 hours are totally wrong while if FV_{LGC} is equal to 0% the power forecast needs of the next 24 hours are totally exact.
We define the FE of the system as the mean value of the FV_{LGC} of all the LGC, that is:

$$FE = \frac{\sum_{i=1}^{N_{LGC}} FE_{N_{LGC}}}{N_{LGC}} \qquad (2)$$

being N_{LGC} is the number of LGCs that compose the system.
Since the CGC tries to grant the power forecast of each LGC, if $P_G(i)$ is the power allocated to the considered LGC at a certain time sample i, $P_F(i)$ is the power forecast at a certain time sample i, and P_{MAX} is the total maximum managed by the considered LGC, we define Forecast Granting Rate of a the considered LGC (FGR_{LGC}) the following expression:

$$FGR_{LGC} = 100 \cdot \frac{\sum_{i=1}^{144} |P_G(i) - P_F(i)|}{P_{MAX}} \quad (3)$$

We define the Forecast Granting Rate of the system (FGR) as the mean value of the FGR_{LGC} of all the LGC, that is:

$$FGR = \frac{\sum_{i=1}^{N_{LGC}} FGR_{N_{LGC}}}{N_{LGC}} \quad (4)$$

We already said that the LGCs control loads divided into high priority loads (HPL) and low priority loads (LPL). Since we suppose that the total delivered power is exactly equal to the total power of the HPL, it is evident that if the LGC request power only for the HPLs, there are always satisfied even if their forecasts are wrong. Since the LGC feed also power to the LPL, it is necessary to define another parameter that indicates which percentage of the power is given to the HPL and which percentage of power is given to the LPL. For this reason we define the Low-High power loads Ratio (LHR) as the ratio between the power of the LPL and the power of the HPL expressed in percentage. The LHR parameter can assume positive values including zero (only HPL power).
In fig.3 the results obtained for the Forecast Granting Rate [%] as a function of Forecast Variability [%] for different values of Low-High power loads Ratio (LHR) are shown.

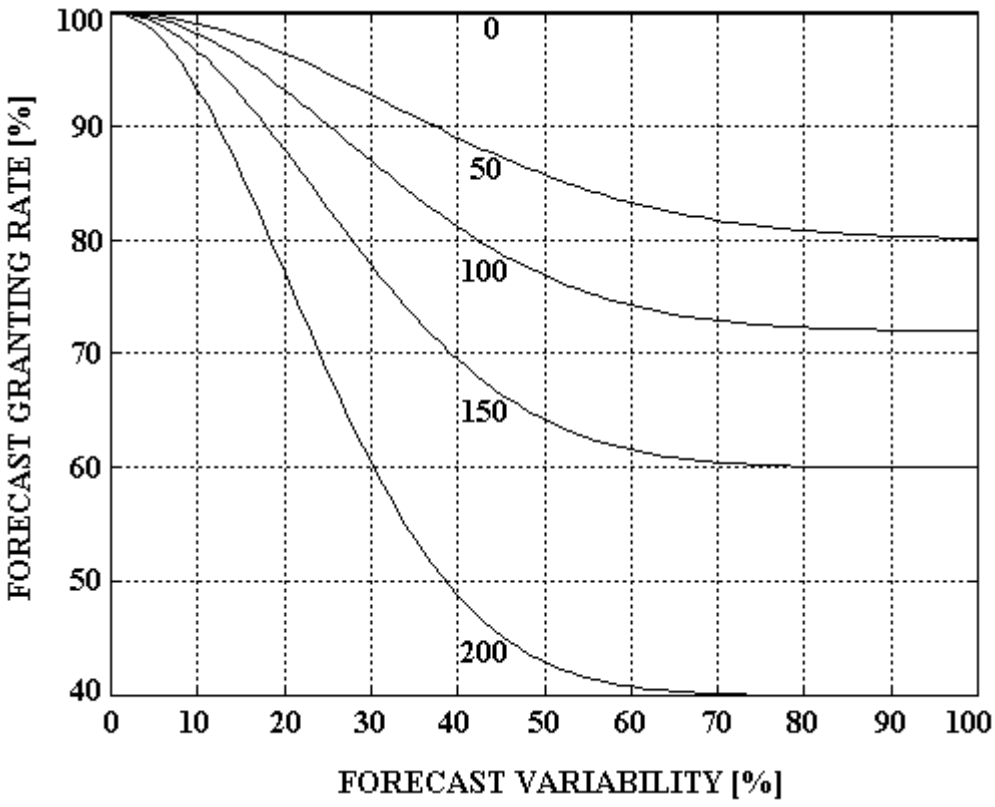

Fig.3 Forecast Granting Rate [%] as a function of Forecast Variability [%] for different values of Low-High power loads Ratio (LHR).

It is possible to see that when the FV is reduced the FGR assume values next to 100%, that is all the LGC power forecasts are satisfied for any values of LHR.
On the contrary, when FV increases, the FGR decreases as steepest as LHR increase. This is intuitive since when FV increases, the electrical power assigned to every LGC tends to not respect the real needs and this effect tends to become dominant when it is necessary to give power to the

low priority loads (greater values of LHR), whereas the total delivered power is not enough for all of them. When LHR=0, that is only high priority loads need power, the FGR is always equal to 100%: this is a particular case since even if the forecast of the LGC are not correct, the total delivered power is always enough to feed all the high priority loads.
Since the CGC needs a certain training period to generate a consistent number of rules to manage and distribute efficiently the electrical power inside the controlled building, it is very important to study also this aspect of the system.
We expect the FGR to reach its final values indicated in fig.3 after a certain number of training days necessary to learn how to behave correctly and we also expect that the mentioned number increases with the FV, that is the higher the variability of the power forecast and the longer is the time necessary to generates a number of consistent rules to manager correctly this uncertainty.
In fig.4 the Forecast Granting Rate [%] as a function of the number of training days for different values of Forecast Variability (FV) is shown, for a Low-High power loads Ratio (LHR) equal to 100. It is obvious that the final value of FGR varies with LHR (72% in the considered situation where LHR has been assumed to be equal to 100).
It is possible to see that the CGC behaviour respects the expectations.

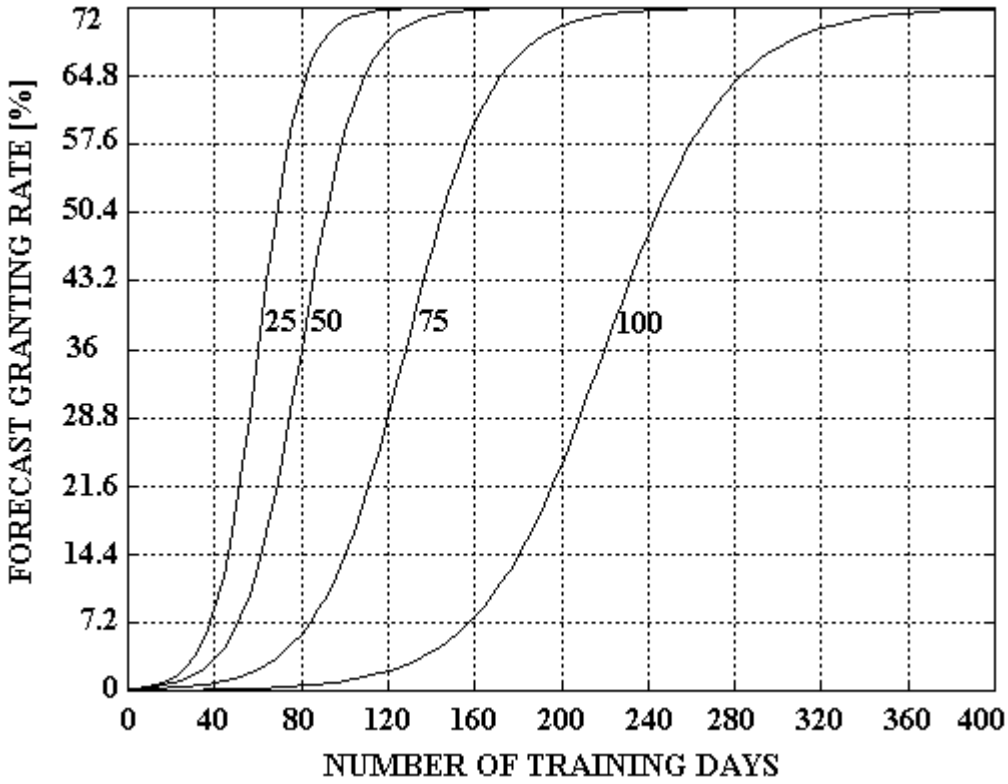

Fig.4 Forecast Granting Rate [%] as a function of the number of training days for different values of Forecast Variability (FV). The Low-High power loads Ratio (LHR) is equal to 100.

CONCLUSIONS

A distributed genetic algorithms system for efficient use of electrical energy has been presented.
It is characterized by an extremely dynamic behaviour that adapts continuously to the electrical power needs of the controlled building, ensuring always the best comfort of the occupants, reducing energy wastes and never overcoming a fixed delivered power.

References

[1] F. Garzia, G.M. Veca, “Management and Control of Energy Flows in Building”, TELESCON 97, Budapest (Hungary).

[2] F. Garzia, G.M. Veca, “Smart Automatic Control of Energy Flows in Building”, DUE 2000, Cape Town (South Africa), 2000.
[3] F. Garzia, G.M. Veca, “Evolutionary Computation and Genetic Algorithms for Energy Management and Conservation”, Telescon 2002, Montreal (Canada), 2002.
[4] F. Garzia, G.M. Veca, “Energy Management using Genetic Algorithms”, Energy and the Environment 2003, Halkidiky (Greece), 2003.
[5] F.Garzia, G.M.Veca, “Optimisation Of Electrical Energy Consumption Using Genetic Algorithms”, DUE 2003, Cape Town (South Africa), 2003
[6] D.E. Goldberg, “Genetic Algorithms in Search, Optimisation and Machine Learning”, Addison Wesley, 1989.