ARTIFICIAL LIFE AND ONLINE FLOWS OPTIMISATION IN ENERGY NETWORKS

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ABSTRACT

In this paper we propose a methodology to optimally manage and online control energy flows over a power network. Such a methodology is essentially based on a artificial life environment. Exploiting some results achieved in the field of evolutionary computing and artificial life environments, the proposed method is intended to combine the ability to select the current best configuration for the network flows with the capability of building an online model for the performance of the network by means of continuous learning the current situation, adapting its internal actions and updating the suggested optimal solution, which controls the process.

With the aim to investigate in the future the possibility of a partially distributed control system, we firstly define the concept of energy district. Hence, we formulate the problem of the online optimal flows management in this type of energy power networks and we finally present some results about the application of the evolutionary control to a real benchmark, the network of the “Casaccia” Research Centre, when critic operating conditions are simulated.

1. INTRODUCTION

Recent blackouts of power networks in USA (August 2003) and in Italy (September 2003) have proved the vulnerability of the main grids, due to difficulties in coping with the increasing level of complexity they present. Much effort is being devoted, in these last years, in developing suitable technologies, able to adapt to unforeseen situation in a short time and to quickly reset the normal operating conditions [1]. None of the existing power grid has been indeed designed and engineered to handle the exploding volume and variety of bulk power transactions associated with the competitive energy marketplace [2]. Besides occasional events (such as blackouts), also the possibility for the network’s topology to vary in time, due for example to new branches being connected or disconnected, as well as the eventuality of sudden changes in users requests, and in general all the issues which imply variation in time of the network model, are factors which require adaptability of the grid’s control system. Moreover a change in conditions at any one location can have immediate impact over a wide area and can give raise to a sequence of cascading failures with consequences in geographically remote regions.

A centralized control, which is the current approach to these problems, does not adapt to such a rapidly varying scenario and it turns out to be as slow as expensive [3].

The line we want to present in this paper consists in distributing control over simpler, smaller, highly connected subparts of the whole network, which we call energy districts. Each energy district is intended to be connected with the rest of the network (that is to say with the national provider) with very few links, and to be governed only by an internal, fast, adaptive and flexible controller. Each district can host small (typically renewable) power sources, able to fulfil a part or the total power request of the users it serves. A crucial requirement to achieve such a local control is to know information about the district, such as the topology, the dissipation, the characteristics of the loads, the users requests and their satisfaction function. In turn, the controller has to be able to optimally manage ordinary resources flows and to quickly recover a good global efficiency in the district, whenever a failure in the main supplying network might occur. This latter property is usually addressed with the term self-healing [4]. The global behaviour of the whole network is supposed to emerge from the composition of the local optimal control policies inside each district and to be optimal as well.

In this paper we present a possible implementation of this type of local controller, based on artificial life. This choice is due to the fact that, in the literature of this field, several online dynamic optimisation and control problems have been successfully studied and solved. In particular, we want here to extend the approach of the so-called evolutionary control methodology.

2. THE METHODOLOGY

In the following we want to describe the evolutionary control approach for optimisation of complex processes. With the term ‘complex’ we address each kind of high-dimensional, highly correlated, non linear dynamical system, for which it’s not possible to have an exhaustive knowledge of the mathematical model. Therefore, in order to achieve continuous performance optimisation and online control for these systems, we have to consider a class of dynamic optimisation methodologies which could allow a continuous updating of the current control solution, depending on the evolution of the system itself.

In this paper we want to propose an approach, the evolutionary control, to solve the problem of online management of flows in an energy power network.

The core of the system is an artificial life environment, which is a 2-dimensional lattice, where several interacting particles move around, each representing a possible solution of the global task we are facing. During their life, individuals meet, struggle and reproduce, mutating in the offspring the solution they are carrying, in order to allow the whole environment to continuously better the current best solution. The artificial life environment is put into the feedback loop which controls the process, so that it continuously acquires measurements of the output of the system it's controlling and updates the relevant model. As a consequence, it is capable to follow the possibly unpredictable process evolution and to adapt its consequent behaviour taking the new operating conditions into account.

In the following we will address the value of the optimisation function in the current solution with the term fitness.

As we said, the artificial environment is a two-dimensional lattice in which a randomly generated initial population of potential solutions to the problem is randomly distributed. Each individual is characterized by three fields: the state, the genotype and the information about the solution it carries. The state takes into account all those characteristics that change during its life, such as for example the position in the 2D space. The genotype stores all the characteristics that do not change during the evolution, such as the mutation rate or the probability to reproduce.

Further details of this algorithm can be found in [7].

The optimisation power of this algorithm has been shown in several applications, ranging from static benchmarks, such as the TSP or some well known test functions [5], to dynamic real world problems, such as the online control of a waste incinerator plant [6] or the online optimal regulation of the oscillation amplitude in a chaotic circuit [7].

3. THE PROBLEM

The evolutionary control approach described in the previous section allows us to tackle a wide class of dynamic optimisation problems. Among them it is possible to formulate the one we want to deal with in this paper, the optimisation of energy flows management in a power network. As we said in the introduction we would like to distribute the control of a power network to lower dimensional, almost autonomous sub-networks, the energy districts.

The energy district can be regarded as a simple network, made up of few nodes, highly interconnected each other, with some autonomous sources of energy (typically renewable), but with few (usually one) connections with the rest of the whole network. The "Casaccia" Research Centre, near Rome, is an example of district, hosting a co-generator and a photovoltaic system, being connected to the national electric backbone and to the emergency diesel engines, and serving about twenty cabins, which in turn satisfy the request of around 2000 users (fig. 1).

In this paper we present optimal energy flows management for the "Casaccia" energy district when some critical operating conditions are simulated. The goal we want to pursue is the maximization of the satisfaction of users together with the minimization of either the energy production or its waste. In the framework of a distributed control system, the management of this type of network has to be locally achieved, so that the global performance of the whole network emerges from the joint rules of the single districts.

The problem can be formulated in a rather simple way, given that we make some assumptions. In particular, we assume to know the two function which express the user's requests over time and the relevant level of satisfaction. We assume the network is built only by three kinds of elements: the source, just supplying power to the network; the user, just absorbing power on the basis of its needs; the node, just connecting the different branches of the network and having the total output flows equal to the total input ones.

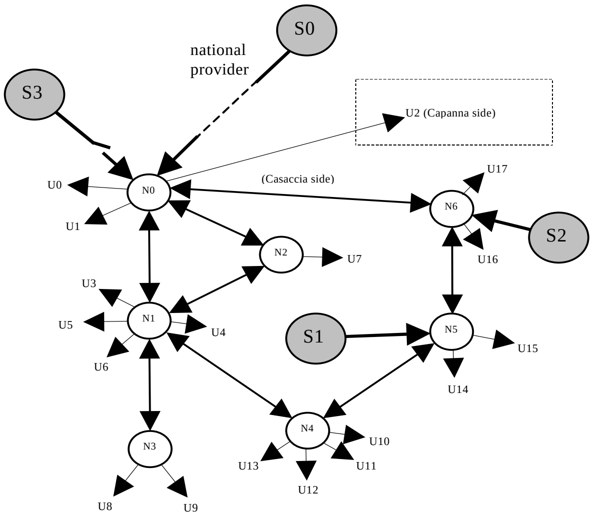

Figure 1. Topology scheme for the "Casaccia" energy district

Let S be the number of sources, U the number of users, N the number of nodes and k the discrete time step. Under the above assumptions the adjacency matrix of the network can be considered in a reduced form, which we call T, having S+N rows and N+U columns. The generic element $T_{i,j}$ is equal to 1 if there is a link between the i-th node and the j-th one, 0 otherwise. We can further consider other three matrices with the same dimensions, carrying information about the links of the network:

- $X(k)$, storing the current flow,
- L , storing the length of each link, and
- M , storing the maximum capacity allowed on each link.

We now define the admissible set $D \subset \mathbb{R}^{(S+N)(N+U)}$ for the optimisation variables, $X_{i,j}(k)$. First, they have to belong to the range $\left[0, M_{i,j}\right]$, $i = 1,2,\dots,S+N$, $j = 1,2,\dots,N+U$. Furthermore, if we denote with $P_l(k)$, $l = 1,2,\dots,S$, the maximum power available at the *l*-th source at time *k*, we have the additional limitation $\sum_{j=1}^{N+U} X_{l,j}(k) \le P_l(k)$, $l = 1,2,\dots,S$. The last limitation we consider is due to the hypothesis we made about the sum of the flows entering a node. To have it null we have to set $\sum_{j=1}^{N} X_{i+S,j}(k) = \sum_{j=1}^{N} X_{j+S,i}(k)$, $i = 1,2,\dots,N$. Hence, the admissible set *D* of the problem turns out to be convex, compact and defined by $2S(S+N)(N+U)$ inequalities and *N* equalities.

In order to define the cost function let $r(k)$ be the *U*-dimensional vector of the users' request at time *k*. We can consider the following function to express the cost of non efficient flows distribution among users:

$$J_e(X,k) = \sum_{j=1}^{U} p_j(k)\left(\left(\sum_{i=1}^{S+N} X_{i,j+N}(k)\right) - r_j(k)\right)^2, \qquad (3.1)$$

where $p_j(k)$ weights the priority level of each user at time *k* and we consider supplying less than required as costly as producing more than what is required.

To take the presence of different power sources into account, we let $c_i(k)$ account for exploitation cost at time *k* of the *i*-th source and introduce a production cost:

$$J_p(X,k) = \sum_{i=1}^{S} \sum_{j=1}^{N+U} c_i(k) X_{i,j}(k). \qquad (3.2)$$

Last, we consider a dissipation cost, which we assume to be linear with respect to the length of each link:

$$J_d(X,k) = \sum_{i=1}^{S+N} \sum_{j=1}^{N+U} L_{i,j} X_{i,j}(k) \qquad (3.3)$$

For our purpose, the resulting global cost function is the sum of these three terms and the problem can be formulated as follows:

$$\min J(X,k) = J_e(X,k) + J_p(X,k) + J_d(X,k),\ X \in D. \qquad (3.4)$$

Problem (3.4) is the constrained minimization of a convex function over a compact (high-dimensional) set. To face this kind of problems with a numerical algorithm, we consider sequential minimizations of penalty functions, punishing violation of the constraints according to a decreasing factor ε. Thus we have a sequence of new cost functions to be minimized in $\mathbb{R}^{(S+N)(N+U)}$, defined as follows:

$$\begin{aligned}
&\min J'_n(X,k;\varepsilon_n) = J(X,k) + \\
&+ \varepsilon_n \sum_{i=1}^{S+N} \sum_{j=1}^{N+U} \max\{0, -X_{i,j}(k)\} + \varepsilon'_n \sum_{i=1}^{S+N} \sum_{j=1}^{N+U} \max\{0, X_{i,j}(k) - M_{i,j}\} + \\
&+ \varepsilon''_n \sum_{l=1}^{S} \max\left\{0, \sum_{j=1}^{N+U} X_{l,j}(k) - P_l(k)\right\} + \\
&+ \varepsilon'''_n \sum_{i=1}^{N} \left| \sum_{j=1}^{N} X_{i+S,j}(k) - \sum_{j=1}^{N} X_{j+S,i}(k) \right|
\end{aligned}$$

The new problem turns out to be not convex any more, being J' not continuously differentiable. This approach, as a consequence, requires non standard methods for numerical optimisation and this is another issue which leads to choose evolutionary computation techniques.

4. EXPERIMENTAL RESULTS

The case study presented in this paper deals with the simulation of a failure in the connection with the national service in the "Casaccia" energy district.

We considered each cabin as an end user of the network and we provided it with a time varying power request, given by the data we had about a work day in the centre. We assigned each user a priority level with respect to the others in order to optimally manage resources in case of scarcity. We then considered the cost for sources to produce energy. To this purpose, we considered real data about either the operating cost or the availability during the day of each of the four sources in the centre (see figure 2), the national provider S0, the co-generator S1, the photovoltaic system S2 and the emergency diesel engines S3.

We let the controller find the optimal set point for each power source and manage the flows over the links of the network. It's worth to point out that, as we will show, the solution we found in this case satisfies all users requests, exploiting more intensively the cheaper sources (S1 and S2) with respect to the more expensive ones (S0 and S3). Hence we can by now say that the basic control we were asking for is achieved.

While the task of normal conduction is being accomplished, we simulate an interruption in energy supply from source S0. As we show in fig. 2, the controller suddenly reacts and switch on the emergency power source S3, rearranging the flows on the basis of the priority in users connected to the district.

In fig. 3 we plot the performance of the optimisation process. We considered to let the artificial life environment evolve over 3000 cycles before sampling the new users request.

When there is the drop in S0's supply, there is a consequent drop in optimisation performance, which is partially recovered in a very short time, managing at the best the unexpected scarcity of resources.

When some time is elapsed, we establish again the connection with S0 and the control system switch off the emergency source and restart its optimal policy of flows management. In fig. 4 we show the plot of the total requested together with the total furnished power. It's interesting to notice the difference between the two types of conduction.

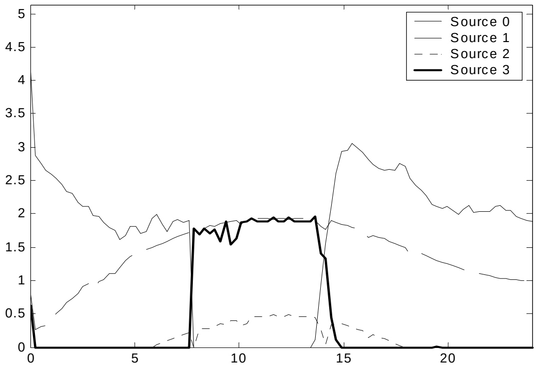

Figure 2. Power supplies from the 4 sources during the day

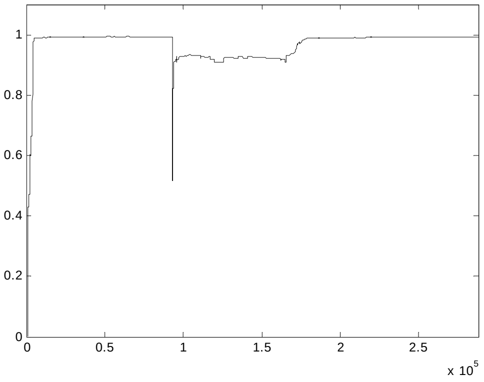

Figure 3. Performance of the optimisation process

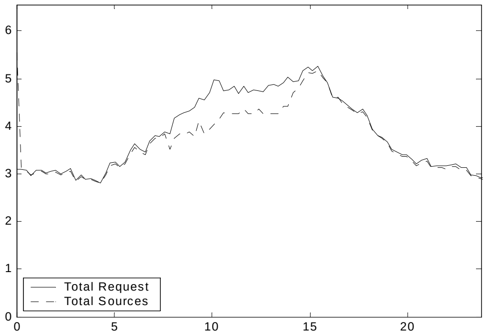

Figure 4. Total requested and total furnished power

5. CONCLUSION

In this paper we presented a possible application of the evolutionary control methodology to the online optimisation of an energy network.

We firstly introduced the definition of energy district to distribute control of the whole network to smaller and more flexible subparts. Then we sketched the main issues of the evolutionary control methodology. Next, we formulated the mathematical problem of online rearranging flows in a generic network in order to optimally fulfil users requests and to minimize managing costs. Last, we presented an experiment in which we simulated a failure in the main supply of the power network of the “Casaccia” R.C. energy district, letting our control system to adjust the set points of the sources and to distribute the available resources among users.

Experimental results showed the effectiveness of the proposed approach in managing the network in normal operating conditions, as well as a good adaptivity of the control system in case a critic event occurs.

Further investigations are strongly required about the reliability of this type of control strategy, possibly taking the network dynamics into account. Finally, the global emerging control of the whole network, arising from grouping all the districts’ control rules together has to be proved to be consistent.

6. REFERENCES

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