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ANN Residential Load Classifier for Intelligent DSM System

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Abstract - Demand-Side Management (DSM) systems have became common in both industrial and homely applications. Basically, these systems help the customers to use electricity more efficiency. Commercial DSM systems are based on the knowledge of instantaneous load power request and, using a priority table, they make their choice. These approaches embed low-level intelligence, hence they can guarantee only coarse results. In this paper an ANN-based residential load classification component to use in the DSM System is described. Aim of the DSM is to prevent cut-off from happening and to schedule loads in a prioritized mode. By means of an associative memory, each socket tap is capable of identify the connected load from a table of "known devices". The eventual misclassification that may arise during the guessing phase is specifically handled by a new training phase. The time the system spends responding to the wrong classification and reacting to it is generally shorter than the time required by the provider's meter to detect the exceeding of the power limit.

Keywords – Demand Side Management, Hopefield net, energy saving, energy efficiency

I. INTRODUCTION

Sudden household current cut-offs due to the exceed in electrical power consumption is a quite ordinary event that can occur in some countries or regions where the local electric provider guarantees the availability of only a limited current flow per time unit. This happens because users may not have precise information about power consumption in household electrical appliances, but only a fuzzy knowledge of them. Individual electrical appliance uses a different quantity of power and often does not follow energy saving guidelines or load balancing, obviously even if every important issue is seen from a macroscale perspective everything depends on contingent needs. In the latest years, however, people seem to be more sensible towards environmental issues and more responsible about correct using of energy.

From a technological point of view, IT technology availability aims at making power grids more intelligent, thus minimizing energy waste and improving demand-side load forecasting [5, 7, 12]. In general, this approach is convenient for the electrical companies, which gain profits from load forecasting and peak demand avoidance, but not necessarily involves final users as role players in the process of energy use optimization. On the other hand, the possibility of distributed energy production made available by the ever-growing free energy installations (solar, wind, geothermal,) claims the need for an intelligent energy distribution policy on a small scale. In this sense, providing the final user with an intelligent energy system is not a chimera anymore, but an easy and low-cost possibility.

Demand Side Management (DSM) consists of implementing procedures and measures (both technical and organizational) which help to control, influence and generally reduce electricity demand with an efficiency purpose. DSM aims to improve final electricity-using systems, reduce consumption, while maintaining the same level of service and comfort. In the past many manufacturing industries had proposed simple DSM-solutions based on current sensor and programmable timers, but they cannot be used for complex problems and they are essentially static. Their embedded logic is very low-level and cannot fulfill high adaptive situations.

This paper, in the line of some previous works [1, 2, 3], proposes the use of a low-cost ANN-based component as the classifier element in a DSM system for household load optimization. The choice of the household environment is led by the criticity of the framework that is characterized by a limited number of well-known loads. The load currents are generally near to the maximum granted current. However the proposed system is also well-suited for industrial applications. The system prevents current shutdown from happening by disabling, for an appropriate amount of time, the socket taps that have the lowest priority. Each socket tap is controlled, in a seeming intelligent way, by an agent-based mechanism that shares the knowledge of each load profile among the other agents and reckons the possibility of having future power limit overcome within a given time window. The load classification is accomplished by an associative memory, which constantly compares the actual load profile sensed at the socket tap with the information present in the shared memory.

The paper is organized as follows: Section II focuses on the use of ANN in the literature for load forecasting, Section III describes the objectives that an intelligent system designed

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for domestic load management should have, the constraints that it must accomplish and the type of load profile it has to deal with. Section IV presents the proposed system as a complement to the one previously proposed. Section V summarizes results and depicts provisional studies that may arise from this work.

II. RELATED WORKS

Artificial Neural Networks (ANNs) have been proven suitable and efficient for electric load forecast. A neural network, in fact, is flexible because it can model very non-linear systems and is scalable because it can be easily extended to consider a wide number of inputs of any kind, [9] for example seasonal weather parameters for their ANN-based load prediction. Several authors [4, 6, 10] propose the use of ANNs in forecasting power network behaviour, thus focusing on the energy production and distribution side. [11] instead of focusing their attention on the customer side, modelling the load profile produced by homeowners starting from the load profiles of individual appliances. This approach is defined bottom-up model in the literature because it considers elementary load components as atomic units that compose the total load curve.

The proposed systems is supposed to embed the knowledge of each appliance load curve by means of a training process or simply by acquiring the load curve from a pre-existing database. In the previous work, the authors provided a Multi Agent – based DSM System for the decisory part of the model which schedules the loads during time whereas this work analyses the learning and knowledge managing part. In particular, special attention has been addressed to how the system classifies the loads and the consequence of an incorrect classification and therefore the problems of a wrong prediction on the scheduled activity.

III. PROBLEM DESCRIPTION

The objectives of load management system for residential use should aim at:

- Avoiding power interruption due to maximum power limit exceed
- Giving the user the maximum comfort by using the available power more rationally and cost-effectively as possible

For example, the Italian provider generally offers the homeowners interruptible load tariff within a maximum of 3KW. Other price policies can assure power continuity with a cost dependent on the power consuming level or on that time of the day when the energy is effectively used. In general, if an apartment is furnished with N different appliances each with its load curve, it can be assumed that to avoid current shutdown it must be:

$$\sum_{i=1}^{n} l_i(t) \leq K$$

with $l_i(t)$ representing the i-th active load and K the maximum power limit. The interval time needed by the provider's meter (equipped with a thermal-magnetic circuit) to catch the extra-power demand is in the range of a few seconds (see Figure 1)

The load curve profile of many appliances presents similar characteristics owing to the presence of similar electronic active and passive components. From a wide in-field analysis conducted over dozens of residential appliances it is possible to assume at least these common elements:

- Peak power request, which remains almost constant as long as the appliance maintains its functioning state (for example: heating, washing, drying, etc…)
- Percentage of constant power demand on the total working period

These features can simplify the evaluation of a typical load curve.

The fact that a load curve can be represented as a sequence of constant power requests per time intervals can be observed in Figure 2 where some real domestic appliance load curves are depicted. This means that most of the appliances present predictable load profiles. This assumption may seem incorrect if referred, for example, to the heating case i.e. the time the oven takes for cooking depends on the type of food to be cooked. This limit can be overcome when assuming that there are different programs for the oven: one requiring 20 minutes of cooking, another half-an-hour and so on. There can also be some appliances whose load curve depends on the willing of the user showing a partially unpredictable characteristic, as it happens for the hair dryer. These loads however can be categorized as uninterruptible, that is they have the upper priority and cannot be stopped arbitrarily. Just considering this, it can be assumed that load profiles can be well and easily categorized.

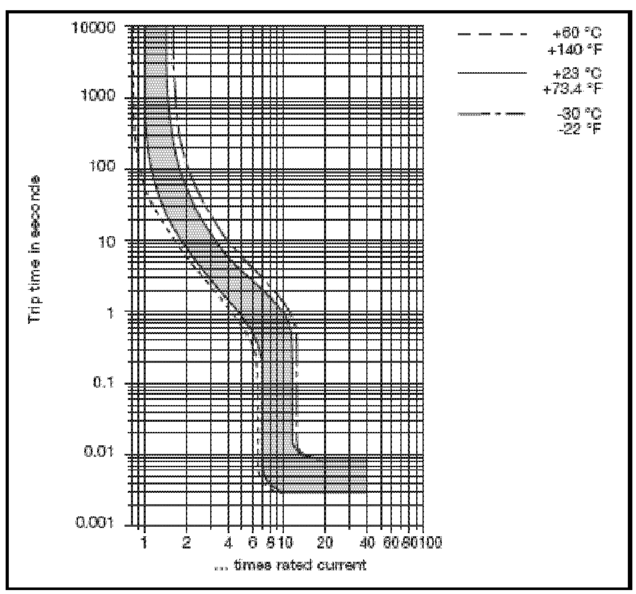

Figure1: typical thermal-magnetic time/current characteristic curve in log scale. Limited extra-currents activate circuit breaker only after many seconds.

This assumption does not solve completely the classification problem of the load profiles. From a wide survey conducted upon a set of common domestic appliances (ovens, irons, dishwashing machines) it may happen that, for a certain inspection window, two or more devices present profiles being very close to each other. This is essentially imputable to the fact that many electromechanical devices are made of the same electrical components such as motors, impedances, wires, etc.. and often requiring similar power. Table 1 and 2 illustrate respectively how computing the correlation coefficients and the corresponding t-statistic values on a benchmark of the aforementioned devices under a 50-samples inspection window taken after 6 sampling times from the starting of the each appliance (the sampling time used is 3 seconds). The *t*-statistic provides a certain measure for the correlation coefficients. The confidence bounds are based on an asymptotic normal distribution of 0.5*log $((1+c_{ij})/(1-c_{ij}))$, with an approximate variance equal to $1/(N\text{-}3)$, where cij represents the correlation coefficient between device *i* and device *j* and *N* is the number of samples used. Low *t*-statistic value (less than 0.05) coupled with a correlation coefficient very close to unit suggests high linear correlation between a pair of load profiles; in particular curve 1 and 2, that have almost the same mean power consumption in the sampling interval considered, seem to be hardly distinguishable. The approach used to assess the classification problem will be discussed appropriately in the proposed system.

Corr. Coeff.	1	2	3	4	5
Curve 1 (iron)	1	0.953	0.897	-0.291	0.384
Curve 2 (electr. oven)	0.953	1	0.918	-0.389	0.4112
Curve 3 (small electr. oven)	0.897	0.918	1	-0.305	0.306
Curve 4 (washing machine)	-0.291	-0.389	-0.305	1	-0.071
Curve 5 (dishwasher)	0.384	0.411	0.306	-0.071	1

***t*-test**	1	2	3	4	5
Curve 1 (iron)	1	~0	~0	0.039	0.005
Curve 2 (electr. oven)	~0	1	~0	0.005	0.003
Curve 3 (small electr. oven)	~0	~0	1	0.031	0.030
Curve 4 (washing machine)	0.039	0.005	0.031	1	0.619
Curve 5 (dishwasher)	0.005	0.003	0.030	0.619	1

Table 1 and 2: correlation coefficient $c_{i,j}$ and correspondent t-test values obtained by comparing the N-sample sized windows of each appliance curve at time instant 6. N is 50. It is noteworthy that, for the inputs used, most of the curve pairs show high correlation.

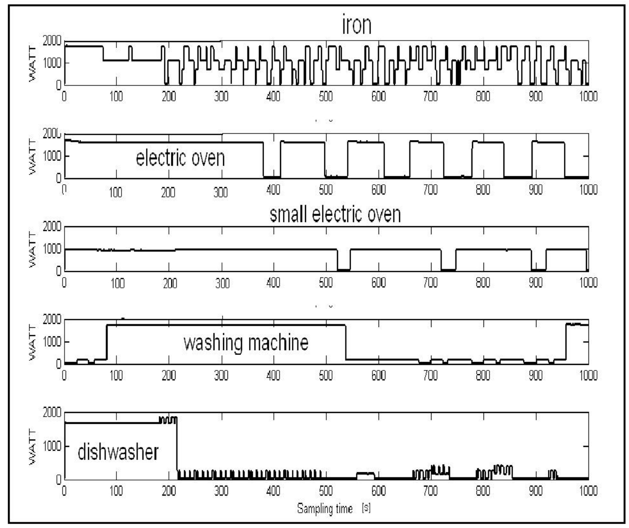

Figure 2: load profiles of five domestic appliances (iron, electric oven, small electric oven, washing machine, dishwasher)

IV. PROPOSED SYSTEM

The proposed residential load management system chiefly consists of two parts embedded in each intelligent socket tap:

- Load identification
- Load scheduling

The former is presented in this section, while the latter has been already presented in [1] and is only rapidly discussed here. Figure 3 gives a schematic block representation of the system.

The system has an a-priori knowledge of all the possible load curves acquired during the learning phase and stored in a Load Matrix. Identifying these curves should not be considered as a real problem since many OEMs provide detailed datasheets with a complete load profile for the appliances they produce. Alternatively, it can be hypothesized that either these curve are the result of a training phase by means of an ANN or they are available on a remote repository accessible via the Internet. Such curves, which can be intended as curve templates, should be as more similar as possible to the actual ones that will be read during the running phase.

The scheduler acts as to prevent shutdown from happening making different priority-based policies competing one another. The scheduler works on the Load Matrix with the templates of only the active appliances (actually, it uses only a subset of the Load Matrix). The scheduler predicts the future profile of the active devices by simply watching at the following values memorized in the Load Matrix. When the scheduler detects a future exceed in power request and recognizing the socket with lowest priority, it will stop the correspondent template at that time; in other words, it disables for a future sampling interval its own socket tap. This modification in the system knowledge is then

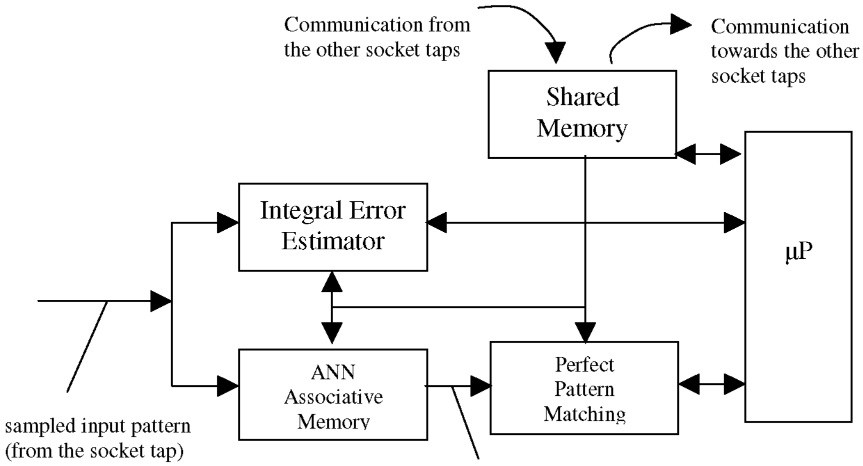

Figure 3: schematic block view of the proposed system.

communicated to the other agents on each tap in order to synchronize the shared knowledge.

The load identification part can be viewed as an ANN-based block managing the following parameters:

- the input frame $[x_i, x_{i+1} \ldots x_{i+n}]$ where x_i is the actual value of current measured at time i
- k, p_k, a, where k is the k-th load, p_k the position of the last element of the k-th load in the k-th load curve and a is a measure of the accuracy for the output assignment.

The input window frame shifts by one position at any sampling time instant and loads the updated value of current. The input frame is presented at any sampling time instant to the block of the associative memory and to the block of the integral error evaluator.

The associative memory (described further in sub-section *A*) outputs a candidate vector which is the memorized pattern closest to the input frame. The proposed candidate pattern is then compared with the corresponding patterns of the active curve templates. If a perfect matching exists, then the system is pretty sure of identifying the curve being read. This implies that the scheduler recognizes the appliance plugged in the tap in one as an active curve in the Load Matrix. On the other hand, if the matching were not successful the scheduler would add a new curve with a constant profile equal to the maximum value of the candidate pattern (worst-case approach) in the Load Matrix.

Generally, during the running phase, k parameter is supposed to remain constant until the appliance is plugged in, but actually some classification problems may arise due to misclassification problems as it has been stated in the previous section. The output parameter p_k ,instead, is supposed to increase during time in accordance with an embedded clock that is common to the scheduler part isofrequent with the sampling time. At any sampling time the scheduler shifts the load matrix by one position updating the knowledge of the future load events. This would mean that, in normal conditions, the scheduler has a perfectly coherent knowledge about the future values of the load for any appliance. However, it may happen that, for some reasons, an actual load curve differs from the template memorized in the Load Matrix. This brings an error and then a parameter output, which can increase during time. If the error between the measured curve and its supposed template is negligible, there is no need to collect again the output of the associative memory. The net will continue to output candidate patterns, but they will not be taken into consideration and the output of the perfect-matching block will be discarded.

The integral error can be easily computed as the sum of the differences in the last T time units between the template and the actual curve. If such an error surpasses a given threshold it can be assumed that incoherence between the actual and the load profile curve has been produced, hence a misclassification has occurred. When this happens a trigger action recalls the output of the perfect-matching and resets the integral error to zero.

A. Associative Memory implementation

The load identification part of the proposed system is provided by an Hopfield net that acts as a similarity-based classifier. The net tries to identify which load is plugged into the tap by means of a non-perfect matching between the template curve and the actual one. The memory states (local minima of the energy function provided by the net) are trained at each sampling time with the patterns coming from the inspection window of the active load templates. The load curve is of course a multi-valued array, so that the associative memory needs to deal with multi-valued patterns.

The early use of Hopfield net was initially intended for the storage and retrieval of only binary patterns, particularly of noisy image classification [13]. Afterward, these approaches have been generalised to the case of multi-valued patterns. Various techniques are known in literature to let an Hopefield net deal with multi-valued data. In this paper the simplest approach has been chosen. The sampled input current values are supposed to be first sampled and then quantised with a certain number of bits. The more the bits the better the net responds to the classification task. If b represents the number of bits used, the quantisation interval here assumed is $3000/2^b$ [watt/sample]. Assuming w as the length of the inspection window, the net can be thought as composed of $N = b * w$ neurons.

Once trained with p patterns (memory states), the net is supposed to converge to one of them whenever an input pattern is submitted to it. The number of patterns p that a Hopfield net can memorise without incurring in producing unexpected spurious states is generally chosen ten times less than the number of neurons N (generally it is assumed $p < 0.1 N$). In our experiments $p = 5$, $w = 20$, while the accuracy considerations synthesised in Table 3 and 4 have been carried out assuming a b value ranging from 4 to 8.

Eventually, we consider the hardware feasibility of the proposed net. In fact, one of the major issues concerned with the physical implementation of associative memories is the high number of interconnections among neurons ($b^2 * w^2$). This problem however has been solved in [8] by proposing a parallel binary neural network architecture with only $b * w^2$ interconnections.

	4-bit	5-bit	6-bit	7-bit	8-bit
0dB	0,18667	0,14417	0,1675	0,17417	0,19167
10dB	0,41917	0,35583	0,40833	0,36417	0,37583
20dB	0,555	0,5075	0,54083	0,52	0,58667
30dB	0,6875	0,73	0,81333	0,81583	0,80667
40dB	0,68833	0,71833	0,93167	0,95167	0,98583
50dB	0,68833	0,72	0,95333	0,98833	1
60dB	0,68833	0,72	0,95833	0,99583	1

Table 3: incidence of signal-to-noise ratio (in dB) and number of binary digits on the recalling performance of the associative memory. Values are percentages ranging from 0 to 1 (1 corresponds to 100% guessing). Such values are computed as mean of nearly 250 recall attempts, equivalent to about 2-hour period of time of system working. For this simulations all five load curves of Figure 2 have been supposed to be plugged contemporarily in one socket tap each.

B. Accuracy considerations

The accuracy of the prediction, that is the correspondence of the template with the instance actually measured at the socket tap, influences the accuracy of the intelligent load control supplied by the scheduler. A good parameter to estimate this last uncertainty parameter is the time when the scheduler forecasts a future critical condition. This, in absence of errors between the two curves, is practically coincident with the length of the forecasting window. In fact, if the template and the actually measured curve are the same, the scheduling mechanism is able to detect in advance (within the inspection window) the future critical condition and makes its own corrective actions. These require a shorter time in comparison with the sampling frequency, then, once run at steady state, the scheduler forecasts a critical condition many samples (practically the number of samples in the inspection windows) beforehand. On the other and, if the two curves are moderately different, the next predicted critical condition will be often reset to zero or low values many times due to the triggered action. However, the time spent to classify the curve and make a forecast is generally shorter than the time necessary to the provider's meter to detect the extra-power demand so that, in practice, shutdown should be always avoided. Providing that the scheduler stops the current flow in order to prevent cut-off from happening thus altering the input conditions, a wrong classification may propagate a closed-loop error. This aspect goes beyond the scope of this paper and will be dealt in a further work. In this paper we limit ourselves to investigate the classification performance of the associative memory.

It is fairly evident that the accuracy of the prediction is strongly dependent on the recall ability of the associative memory. Simulations have been carried out with the following parametric assumptions:

- White gaussian noise incidence (measured in dB of signal-to-noise ratio per sample) on the power amplitude of the sampled input patterns.
- Duty cycle variation of people-driven appliances (like iron) expressed as poisson distributed mean number of delay samples that exceed the expected wave front drop/rise event

samples	4-bit	5-bit	6-bit	7-bit	8-bit
0	0,68833	0,72	0,95833	0,99583	1
5	0,68	0,7125	0,94833	0,9875	0,9925
10	0,67083	0,68917	0,93333	0,97417	0,98667
15	0,66667	0,675	0,91917	0,965	0,98
20	0,665	0,68667	0,91583	0,96917	0,97667
30	0,65167	0,66417	0,89667	0,96833	0,98167
40	0,64667	0,65083	0,87917	0,94333	0,95083
50	0,6425	0,64	0,8725	0,905	0,92583

Table 4: incidence of delayed wave front drop/rise events in terms of extra samples on the recalling performance of the associative memory. First row has the same value as the last row in Table 3: in both cases the input signal is considered practically noise free. The simulated input conditions are the same of Table 3.

Table 3 and 4 summarize simulation results in relation to the above parameters considered with different numbers of binary digit quantisation (hence different number of neurons for the net). Results show that the associative memory has a high guess rate with an 8-bit quantisation, in normal operating conditions (SNR > 40 dB), with moderate discrepancies between real curves and their memorised templates. This ensures a good quality classification that allows the scheduler to work on reliable data.

V. CONCLUSION

This work proposes ANN-based residential load classification component to use in a low-cost DSM system for residential load management. The DSM aims at avoiding current cut-off due to extra-power request in a prioritised mode. A simple architecture for the system has been presented. The proposed system makes use of a Hopfield associative memory for the classification part. Considerations on the number of neurons and on the accuracy of the classification have been discussed. Simulations prove that it suffices a low number of binary digits with a tolerable signal-to-noise ratio to have good recall responses. This makes the system implementation highly feasible.

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