Fair Allocation of Distribution Losses based on Neural Networks

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***Abstract*— In a competitive energy market environment, the procedure for fair loss allocation constitutes a matter of considerable importance. This task is often based on rough principles, given the difficulties on the practical implementation of a fairest process. This paper proposes a methodology based on neural networks for the distribution of power distribution losses among the loads. The process is based on the knowledge of load profiles and on the usual consumption measures. Simulations ere carried out for a typical MV network, with an extensive variety of load scenarios. For each scenario, losses were calculated and distributed by the consumers. The allocation criterion is established assuming a distribution proportional to the squared power. Finally, a neural network is trained in order to obtain a fast and accurate losses allocation. Illustrative results support the feasibility of the proposed methodology.**

***Index Terms*— Distribution systems, loss allocation, load profiling**

I. Introduction

In the large majority of countries, the methodology adopted for loss allocation is based on somewhat simplistic principles, given the difficulties on the practical implementation of a fairest process. It is known that stamp like or fixed tariff methods may induce severe differences between the real losses caused each consumer and the losses allocated *de facto* by the application of the tariff legislation. In Norway, for instance, [1,2] loss allocation is based on Marginal Loss Factors and Point of Connection Tariff, meaning that the same consumption (and losses) on different zones would be charged different amounts. In other countries (like Portugal [3], the distribution of losses for tariff purposes is based on loss coefficient factors for each voltage level. Within each voltage level, losses are assigned by multiplying the energy measures (peak hours, valley hours, intermediate) by the corresponding loss factor. This method assumes (inaccurately) that losses are proportional to the consumption. On the other hand, the shape of the diagram is only partially considered. For instance, if two consumers present exactly the same consumption within each period (peak, valley and intermediate hours) they will be charged the same amount of losses even if one of them has, for instance, all the peak consumption concentrated in a single hour, when the other presents a constant consumption within all the peak period.

This paper discusses the loss allocation problem and proposes a new methodology, conceived to deal with the following concerns. The first one is fighting for a fairer distribution of network losses, trying to assign to each consumer a closer match to its factual losses contribution. For this purpose it's important to consider not only the consumer's load in a specific instant and its relation with the other loads, but also its typical load evolution (diagram). The next section discusses the losses distribution problem and clarifies the meaning of "factual losses contribution". The second major concern is related to the conception of a fast and reliable process to perform the loss allocation according to the previous consideration. The methodology to be established must be able, not only to allocate a proper loss amount to each consumer, but also to do it on the basis of the billing data and not on results output by load flows or other power systems analysis algorithm. For real dimension systems the eventual need to run a large number of load flows (for each system state) would be a hard constrain, given the related processing time required.

The structure of the paper is the following. The next section discusses the loss allocation problem and the need of adopt some assumptions (*e.g.* principle of quadratic distribution). Then in Section III, the proposed methodology is described. Section IV presents the results attained. The conclusions and references complete the paper.

II. The Loss Allocation Problem

Loss allocation constitutes an essential tool for efficient planning and operation of power systems, particularly in a free energy market environment. The yielding of a given portion of network losses to a given consumer remains nowadays an open problem. Distinct approaches are being proposed or adopted by different authors and regulatory authorities [4-13].

The first phase of a loss allocation setup study is the estimation of total system losses, usually in a yearly basis, which may be achieve through the annual energy balance.

Manuscript received March 30, 2007.

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However, it turns progressively more difficult to do this work of estimation as one steps down to lower voltage levels of the power system. In fact, even for a single load regime (peak hours, for instance), losses depend of network electrical parameters, lines length, consumptions' simultaneity and on the geographical distribution of the consumption.

For a matter of illustration of this last aspect, consider a reference feeder with length L, a total resistance R, connected to a single load I. Assume now (neglecting voltage deviations) the cases where the same load may present the following types of distribution: uniformly growing, uniformly distributed and uniformly decreasing. The results of this study (Table I) are elucidative of the large losses variation for the same total load.

TABLE I
LOSSES VARIATION FOR THE SAME TOTAL LOAD (ILLUSTRATION)

Case	Load in the end	Growing load	Uniform	Decreasing load
Load at the emission	I	I	I	I
Load at the beginning	0	0	I/L	2.I/L
Load in the end	I	2.I/L	I/L	0
Losses	$R.I^2$	$8(R.I^2)/15$	$(R.I^2)/3$	$(R.I^2)/5$
Relation	1	0.533	0.333	0.2

As shown, the loss variation interval may be substantial, making the option of loss characterization by sampling virtually impossible, given the huge amount of data required (a lot of nets, a lot of distributions, a lot of loads,...). Being so, the most common approach is based on the analysis of typical networks, for different feasible load regimes and different consumer samples.

Concerning to the assignment of losses to consumers, there are other issues to be considered, like the losses quadratic nature and from the presence of other consumers. For instance, consider a feeder is connected to a single consumer. If a second consumer of equal power is added, the losses will result four times higher (even higher, if one considers the voltage effect), i.e., the first consumer will see its losses doubled just because of the presence of the second consumer. Being so, the stipulation of a fixed percentage of the power (or the more sensible criterion of squared power) as loss contribution should always be figured out in terms of mean behaviour.

III. METHODOLOGY

The proposed approach develops through the following phases:

1) Extensive simulation of a large variety of scenarios in a study network. In this research a real typical MV network was used. Consumer data, namely load diagrams were driven from the historical data base and used to characterize network loads in the different scenarios;
2) For each scenario, total network losses are computed and allocated to consumers following the quadratic distribution principle (a allocation rule that is at the same time fair and practical);
3) Data collection. Inputs and results from previous steps are gathered in a data set. Once this phase is completed, one has a large set of system states and the losses attributed to each consumer for each scenario. Setting a time basis (a day – 24 hour load diagrams, for instance), a set of diagrams' factors (load factor, loss factor, etc.) are determined for each consumer, and the corresponding losses added up over the considered period;
4) Training artificial neural networks (ANN) for fast and automatic loss allocation [15-20]. These ANN use as inputs the available billing information and diagrams' characterizing factors. Note that real diagrams are not always available, especially for low voltage consumers. However, diagrams' characterizing factors are usually obtainable: either because they are accessible in the billing data or because they may be driven from load profiling. The procedure is explained later in this paper;
5) Results analysis. Assessment of ANN performance indexes. Comparison of results when using diagrams' characterizing factors driven with the ones that result from load profiling.

Load flow analysis was performed using PowerWorld software [21,22].

A. *Data gathering*

As mentioned previously, one of the first phases consists of gathering data, able to implicitly characterize the consumers' loss allocation under a variety of scenarios. These scenarios were obtained as follows. The MV network under analysis (Fig. 1) feeds 23 consumers, for which there is a historical record of its load evolution (24 hour diagrams) for a period of 819 days (about 27 months), resulting in a total of 19 656 hours. For each hour, each consumer is assigned the corresponding hourly value and a load flow is carried out. Then, the total losses are evaluated and distributed by the consumers following the quadratic distribution principle.

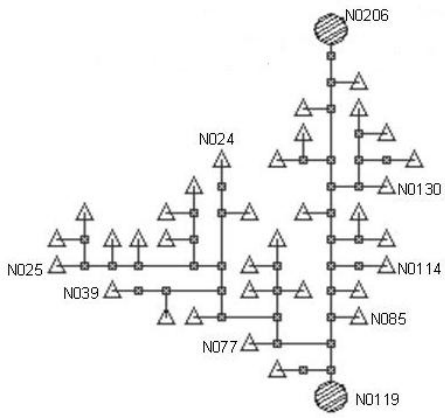

Fig. 1 Simplified scheme of the power net under study

The next step consists of computing, for each day and consumer, their diagram characterizing factors and aggregate

its daily losses. Once this phase is completed, it's possible to assemble a pattern set, where the outputs are the losses to be assigned. As inputs one may consider not only the diagram characterizing factors but also the total energy (in a monthly base, for instance), an important variable to be considered in this problem.

B. *Diagrams' characterizing factors*

There is a number of factors that may be used to characterize load diagrams. In this study, the following were considered:

Load factor

$$Fc = \frac{P_{av}}{P_{max}} \tag{1}$$

Loss factor

$$Fp = \sum_{h=1}^{24} \frac{\left(P_h / P_{max} \right)^2}{24} \tag{2}$$

Contribution of consumer i to the peak

$$Fcp_i = \frac{P_i\ (h = \text{network peak})}{P_{max}\ (\text{network})} \tag{3}$$

onde $\sum_i cp_i = 1$

Peak occupation factor

$$Fop_i = \frac{P_i\ (h = \text{network peak})}{P_{i\ max}} \tag{4}$$

Each factor allows the observation of a different feature and qualifies the diagram under a distinctive perspective.

C. *Neural networks*

In the proposed methodology, ANN are used for multiregression purposes.

The ANN input/output scheme is presented in Fig. 2.

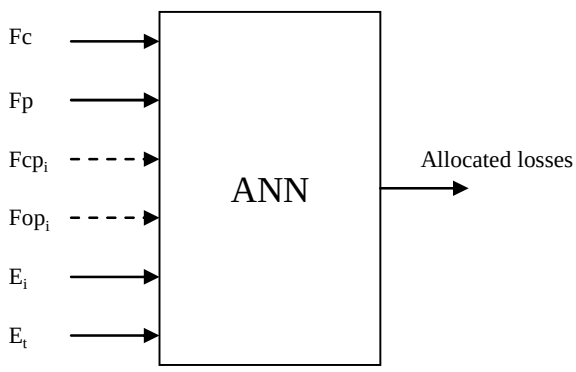

Fig. 2. ANN input/output scheme

Two sets of inputs were tested: in the first case, the inputs were Fc, Fp, E_i (energy consumption of consumer i) and E_t (energy consumption of all the consumers); in the second case, two more inputs were considered (Fcp_i and Fop_i). The idea was to compare the ANN performance for both cases.

As usual, the set of patterns was divided into two subsets: one for training and the other for testing.

The training phase was based in Levenberg-Marquardt algorithm [15-17], although Resilient, Quasi-Newton and traditional Backpropagation have also been tested.

The performance error is characterized in this study by the Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{T_i - R_i}{T_i} \right| x100 \tag{5}$$

where n is the number of testing patterns, T_i is the real output value for pattern i and R_i is the ANN output for the pattern i.

Note that all the performance indices referred in this paper respect to the testing set, in order to characterize appropriately the ANN generalization aptitude.

IV. LOSS ALLOCATION METHODS

This section compares losses allocated to each consumer resulting from three different methods: quadratic distribution, the stamp method and the Portuguese tariff regulation.

It is not in the scope of this paper to present a detailed description of the different principles and techniques that may be used for loss distribution. However, it is worth mentioning that results could vary substantially with the method applied.

Fig. 3 shows the losses allocated to each consumer of the network under analysis, for the three loss distribution methods considered. The abscissa axis contain the load's identification node and the ordinate axis the energy losses in MWh.

r i coincide

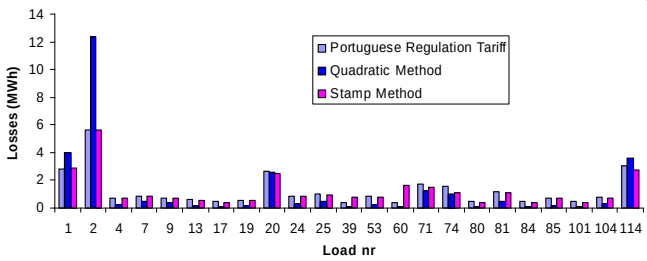

Fig. 3 Losses resulting from different methods

As expected, the Portuguese tariff (based on loss factors) presents similar results to the stamp method. Note that both methods distribute the losses proportionally to the load power, while the quadratic approach considers the squared power. Therefore, the conclusion is that the actual Portuguese regulation tariff (like the stamp method) leads to a situation where the smaller loads are penalized relatively to the larger ones.

V. Results

This section presents the main results obtained in the current research. One starts by showing that ANN can be used to perform automatic loss distribution. In the first studies, the evaluation of the diagrams' characterizing factors is based on the real load curves. Since real load curve aren't always available, a second study was carried out using load profiling to access load diagrams.

The test set consists of 12 months of historical data in a hourly basis.

A. *Using data from real diagrams*

1) *Four inputs ANN*

After several experiences, the ANN architecture that provides the best results was found to be 4-24-10-1: 4 inputs, a first hidden layer with 25 units, a second hidden layer with 10 units and 1 output. Fig. 4 shows the generalization performance obtained in this case considering a monthly basis. In this case, one is assuming that energy consumption is measured every month.

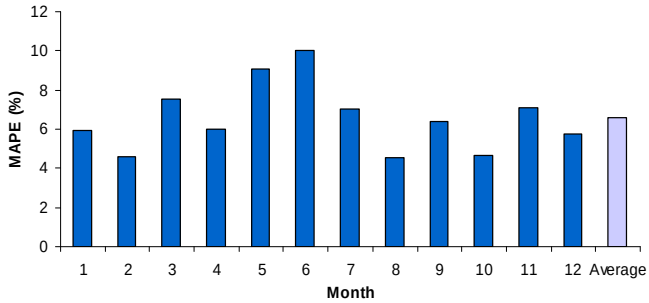

Fig. 4 MAPE obtained with the 4 input ANN, real diagrams, monthly basis

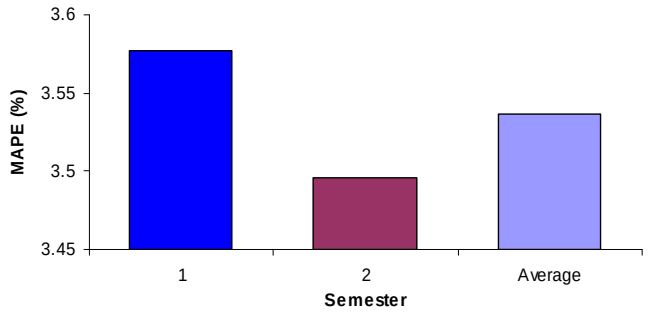

Fig. 5 MAPE obtained with the 4 input ANN, real diagrams, semester basis

The performance errors might also be computed on a daily basis but that wouldn't correspond to the real usual situation, where distribution companies perform real consumption measures every month, semester or even year. That's why the performance errors were also calculated for this time basis (Fig. 5 and Table II).This figure shows the MAPE obtained for the first and second semesters. In this case, the consumers' energy measures are supposed to be acquired at the end of each semester. With a yearly time basis one is using a single energy measure (annual energy consumption) during the test period, while in the monthly case one uses 12 energy measures (monthly energy consumption). Being so, one might expect to obtain better results is the last case. However, an important aspect to be taken into account is the mean effect: in some months, the losses may be estimated above the real and in others below, and the error tends to be smaller for a larger number of months.

Table II
MAPE obtained with the 4 input ANN, real diagrams

Time basis	MAPE (%)
Month	6.55
Semester	3.54
Year	2.85

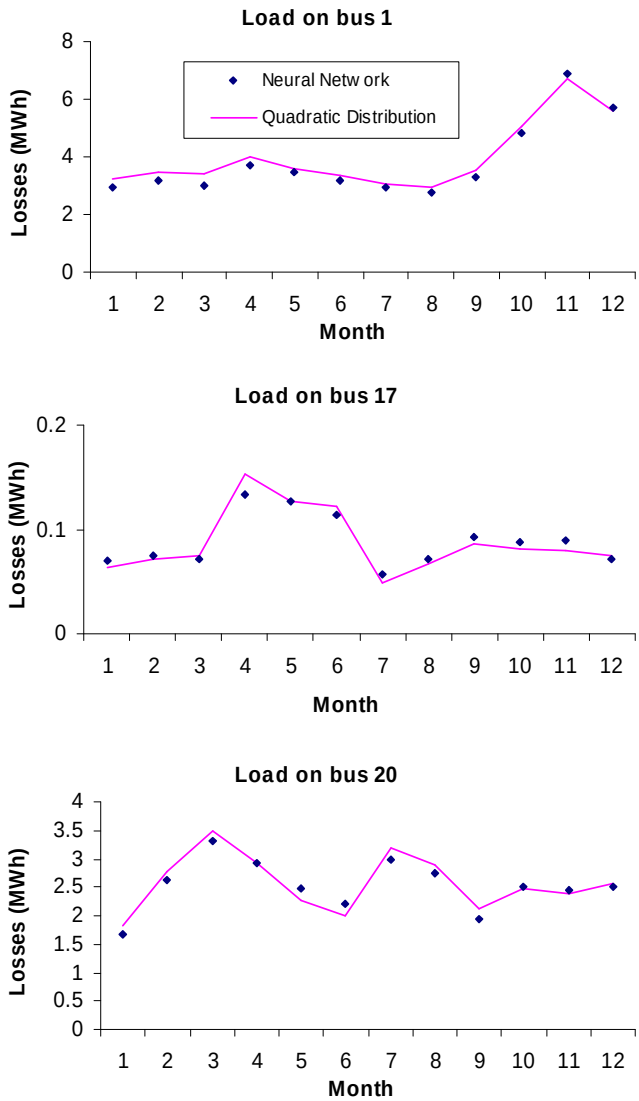

Fig. 6 Comparison between losses obtained with quadratic distribution and losses provided by the ANN, for each month (3 examples)

Fig. 6 shows the losses assigned by the quadratic rule and the ones provided by the ANN, for three consumers and for each month.

2) Six inputs ANN

The procedure followed in this case was identical to the previous one. The final ANN architecture was 6-20-1: 6 inputs, a single hidden layer with 20 units and 1 output.

TABLE III
MAPE OBTAINED WITH THE 6-INPUT ANN, REAL DIAGRAMS

Time basis	MAPE (%)
Month	6.00
Semester	3.67
Year	2.74

Comparing these results with the ones presented in Table II, it is clear that MAPE indices are similar, being slightly lower in the second case for the month and year time basis, and slightly above for the semester case.

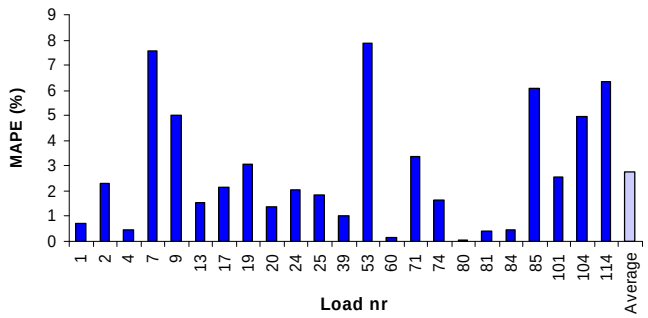

Fig. 7 MAPE for each individual consumer, the 6-input ANN, real diagrams, yearly basis

The MAPE obtained in this case for each individual is portrayed in Fig. 7. The analysis of errors distribution show that the largest errors occur for the smallest loads. This is somewhat expected because, even when the absolute deviation is small, the corresponding percentage error may result substantial.

B. *Using data from profiled diagrams*

The previous section demonstrates that it's possible to perform a fast and accurate loss allocation using data directly driven by the real diagrams. In the absence of load diagrams historical data, the diagrams may be estimated throughout load profiling. The main objective of the present section consists of analyzing the feasibility of this hypothesis. For this purpose, the following steps were considered:

1) Obtaining basic profiles;
2) Applying basic profiles to loads, considering consumers data and energy measures. As a result, profiled diagrams are obtained;
3) Apply the same methodology used in section A but using the profile diagrams instead of the real ones.

Two basic profiles were settled by dividing the consumers into two groups, depending of whether or not annual energy consumption was above 500 MWh. The mean diagram of each group was then undertaken as its basic profile. The basic profiles obtained are shown in Fig. 8.

The profiles set up method used here is rather crude, once profiles are only used to illustrate the methodology: there were no concern about clustering performance or differentiation between workdays, Saturdays and Sundays.

Step 2 consists of obtaining the profiled diagrams for each consumer. This phase involves the adjustment of the basic profile such a way that the energy of the profiled diagram matches the energy measure taken for each period (peak, intermediate, low and super-low). Fig. 9 compares the real diagram with the profile one, of consumer 2 for a given day.

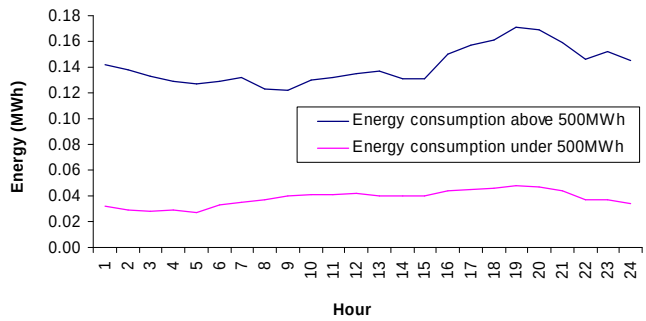

Fig. 8 Basic profiles considered in this study

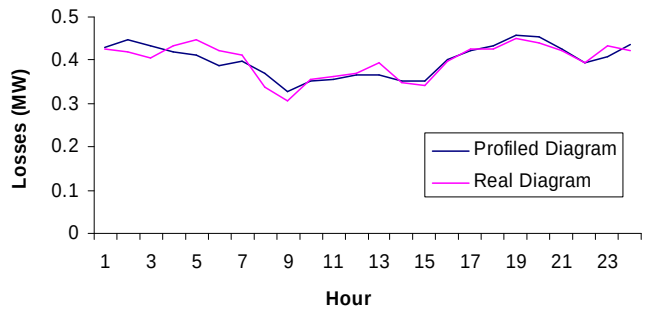

Fig. 9 Comparison between real and profile diagrams on load bus 2

TABLE IV
MAPE OBTAINED WITH THE 6-INPUT ANN, PROFILED DIAGRAMS

Time basis	MAPE (%)
Month	11.09
Semester	9.21
Year	8.02

Table IV synthesizes the results attained in step 3, showing the ANN generalization performance. At first sight, an error of about 10% may be considered excessive. However, a few observations should be made about these results. First, there is

a single consumer (node 9) that contributes a lot to the global error presenting a MAPE of 34.1%, in part caused by a considerable mismatch between real and profiled diagrams. In this case, a more adequate load profiling would contribute to smaller errors. Second, similarly to the previous studies, one verifies that largest errors occur for the smallest loads. Finally, and most important, under the present tariff legislation (using loss factors), the mismatch between allocated losses and the reference losses is considerably higher: for a yearly time basis, about 23% when the reference losses are settled by the stamp method.

VI. Conclusions

This paper present a loss allocation methodology based on neural networks. The research was motivated by the fact that most real systems had adopted simplistic (and usually unfair) loss allocation methods, given the difficulty on the implementation of alternative fairer/practical methods. On the other hand, those methods, like the stamp method, present the advantage of simplicity. However, as long as the energy market becomes more efficient, the higher will be the requirement for higher fairness in all features, including loss allocation principles.

The study carried out on a typical MV network, and with a limited number of consumers, has produced quite encouraging preliminary results, supporting the feasibility of the proposed approach.

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