# DETERMINING THE HARMONIC NETWORK IMPEDANCE MAINLY FOR PLANNING PURPOSES IN LOW VOLTAGE SYSTEMS

**F. Otto** **W. Rupf** **G.Winkler** **J. Meyer**

**DREWAG**
**Stadtwerke Dresden GmbH**
**PF 120731**
**01008 Dresden (Germany)**
**Tel: +49 351 860 4172**
**Fax: +49 351 860 4440**

**Technische Universität Dresden**
**Institut für Elektroenergieversorgung**
**01062 Dresden (Germany)**
**Tel: +49 351 463 5088**
**Fax: +49 351 463 7036**
**e-mail: winkler@eev.et.tu-dresden.de**

## *INTRODUCTION*

*Assessing the voltage quality at the PCC to a customer, commonly the standard EN 50160 is applied. The use of disturbing loads, especially with switching power supplies, causes voltage harmonics in the low voltage networks. An estimation of the harmonic network impedance and the voltage harmonics respectively during the planning is described in the paper. The developed method increases the trust worthy for further planning.*

## BASICS

The equivalent schematic for the connection of a disturbing load to a low voltage network containing harmonics is shown in fig. 1.

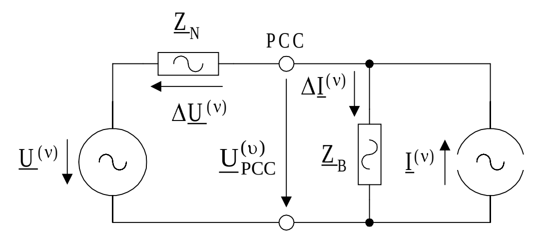


*Figure 1 Schematic for the ν-th harmonics*

Supposing the disturbing load as the only cause of the voltage distortion, the harmonics can be calculated by

$$\underline{U}^{(\nu)}_{PCC} = \underline{I}^{(\nu)} \cdot \underline{Z}_N \| \underline{Z}_B \,. \tag{1}$$

In addition to the injected current harmonics $\underline{I}^{(\nu)}$ at the PCC it is necessary to calculate the impedance of the network topology $\underline{Z}_N$ and the impedance of the consumer topology $\underline{Z}_B$ at the low voltage busbar.

The impedance of the network topology $\underline{Z}_N$ (medium voltage network, medium voltage lines, transformer, low voltage lines) is calculated by known equipment parameters and depends only on the location. The impedance of a complex consumer topology $\underline{Z}_B$, like residential areas additionally depends on time and phase (fig. 2 and 3).

Time dependence results from customer behavior. Dependence from phase line is caused by an asymmetrical customer topology.

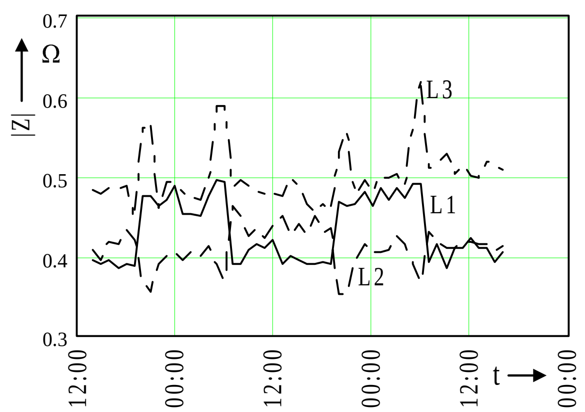


*Figure 2 Absolut value of the harmonic impedance for a residential area topology (525Hz)*

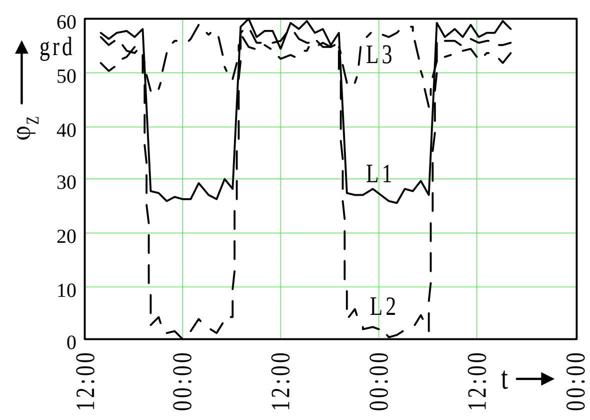


*Figure 3 Phase angle of the harmonic impedance for a residential area topology (525Hz)*

The harmonic network impedance characteristic in low voltage systems is classified in 5 different types (fig. 4) [1, 2].

For a single PCC the type of harmonic impedance characteristic may vary over the time as well as between the phase lines.

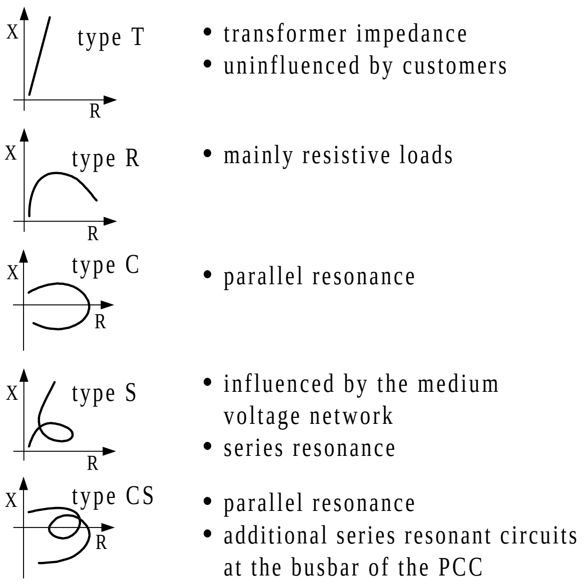


*Figure 4 Types of the harmonic network impedance characteristic [1]*

## METHODS OVERVIEW

For the evaluation of the harmonic network impedance three basic methods are distinguished.

Modeling the low voltage network of a PCC by discrete network elements (resistors, capacitors and inductances) and performing a network calculation for the desired harmonic frequencies is one way to determine the harmonic network impedance. This method is only practicable for a manageable number of loads. Due to the permanent change of loads in consumer topologies with an immense amount of small loads the modeling of a static equivalent network is very difficult. The results of the network calculation are only valid for the specified location, time and phase line. The modeling method is preferably used for worst case analyses, if a limited number of loads has to be connected to a PCC. Also the knowledge of all modeling parameters is supposed.

A statistical evaluation of existing network impedance measurements over a specified time period results in an time-dependent, averaged harmonic impedance characteristic for the regarded consumer topologies. Therefore the statistical method only depends on location and phase line. The accuracy of the results is mainly determined by a careful selection of the chosen consumer topologies. This method is suitable for a general estimation of the harmonic network impedance for several consumer topologies. Enhancing the method by the development of an expert system is not recommended, because of the disproportional effort for maintenance.

A third method is based on neuronal networks, which are extensively used on the field of load forecasting. The method conditional depends on the phase line only and is independent from location and time. A significant advantage of this method is the simplicity of obtaining the necessary input data. A basic condition for the use of neuronal networks is a detailed knowledge of all parameters, which have an influence on the harmonic network impedance. These influencing parameters are input data for the neuronal network.

The features of the different methods are compared in fig. 5.

| depending on: | modeling | statistics | neuronal networks |
|---|---|---|---|
| time | x | | |
| location | x | x | |
| phase line | x | x | (x) |

*Figure 5 Features of the different methods*

Because of it's advantages the method using neuronal networks will be specified in the presented paper.

## PARAMETERS INFLUENCING THE HARMONIC NETWORK IMPEDANCE

Due to the analysis of more than 6000 existing measurements of the harmonic network impedance [3], three categories of influencing parameters are defined (fig. 6).

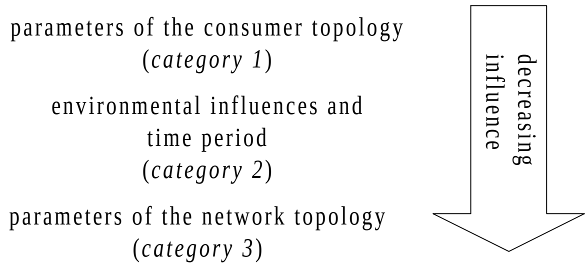


*Figure 6 Classification of the influencing parameters*

### Consumer topology (category 1)

All consumers of a consumer topology are divided in subcategories regarding their behaviors as shown in fig. 7.

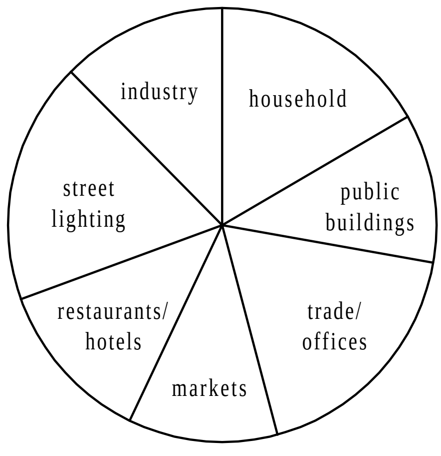


*Figure 7 Subcategories of the consumer topology*

Next the total power consumption of the PCC is split into the subcategories. On working-days the harmonic network impedance mainly depends on the trade/offices and the industry, while at weekends the impedance is almost exclusively effected by households. To take into account different energy sources, the percentage of off-peak storage heatings, hot water tanks and electric stoves needs to be specified.

The necessary input data for the consumer topology results from an analysis of the supplied region and is normally available.

**Environmental influences and time period (category 2)**

Beside the network and consumer topology the harmonic network impedance is influenced by the environment and the time (cf. fig. 2 and 3). Nights for instance are typical low load states mainly determined by a few permanent loads and a possibly connected street lighting. In contrast to this the highnoon at weekends is characterized by many resistive loads (cookers, ...) and the evening especially by switching power supplies of computers or TV-sets. The influencing parameters of category 2 are:

- day of the week
- daytime
- sunset and sunrise time
- temperature (day and night)
- weather

The weather (intensive clouds) as well as sunset and sunrise especially influence the use of lighting, while temperature mainly influences the heating behavior. The combination of temperatures and sunset/sunrise contains seasonal information.

The input data are available from meteorological stations.

**Network topology (category 3)**

The harmonic network impedance may be effected by the topology of the medium and low voltage network (fig. 8).

The influencing parameters shown in fig. 8 are only relevant, when the power consumption of the connected consumers is low. Due to wide cable networks at the low voltage level or the use of reactive-power compensation equipment, resonance's may occur in the low-frequency range.

The necessary input data are mostly available from network diagrams or equipment databases provided by the regional utility.

## FORECASTING ALGORITHM

The forecasting algorithm consists of two steps. First the type of the harmonic network impedance characteristic is determined by a learning vector quantization. To obtain an exact harmonic network impedance characteristic, a specialized neuronal network is used for each impedance type (fig. 4). The algorithm is shown in fig. 9.

The learning vector quantization for the classification of the impedance type is realized by an one-layer neuronal network with supervised learning method. Different typical vectors of input data of each impedance type (so called codebook-vectors) are needed for the learning process. If the learning process has completed the neuronal network is able to decide, which impedance type corresponds with the input data vector. On the basis of this decision the specialized neuronal network of step 2 is selected. For these specialized neuronal networks the supervised backpropagation algorithm is used for the learning process. The algorithm works with variable learning rate and momentum term.

Every input data vector consists of 22 standardized values and represents all influencing parameters introduced in the former explanations. The size of the output data vector depends on the measurement data used during the learning process. Commonly, reactance and resistance of the impedance will be calculated for up to 50 harmonics (50Hz-steps) in the frequency range between 50Hz and 2500Hz.

The plausibility of the input and output data vectors for the

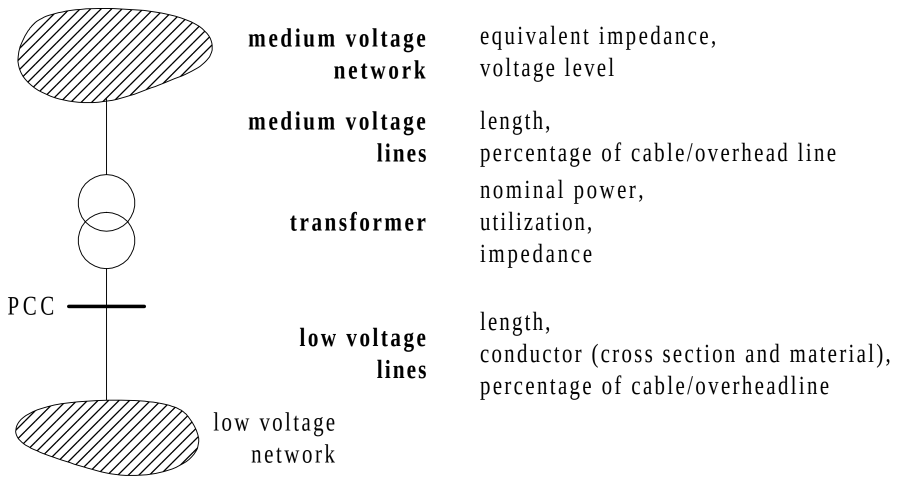


*Figure 8 Subcategories of the network topology*

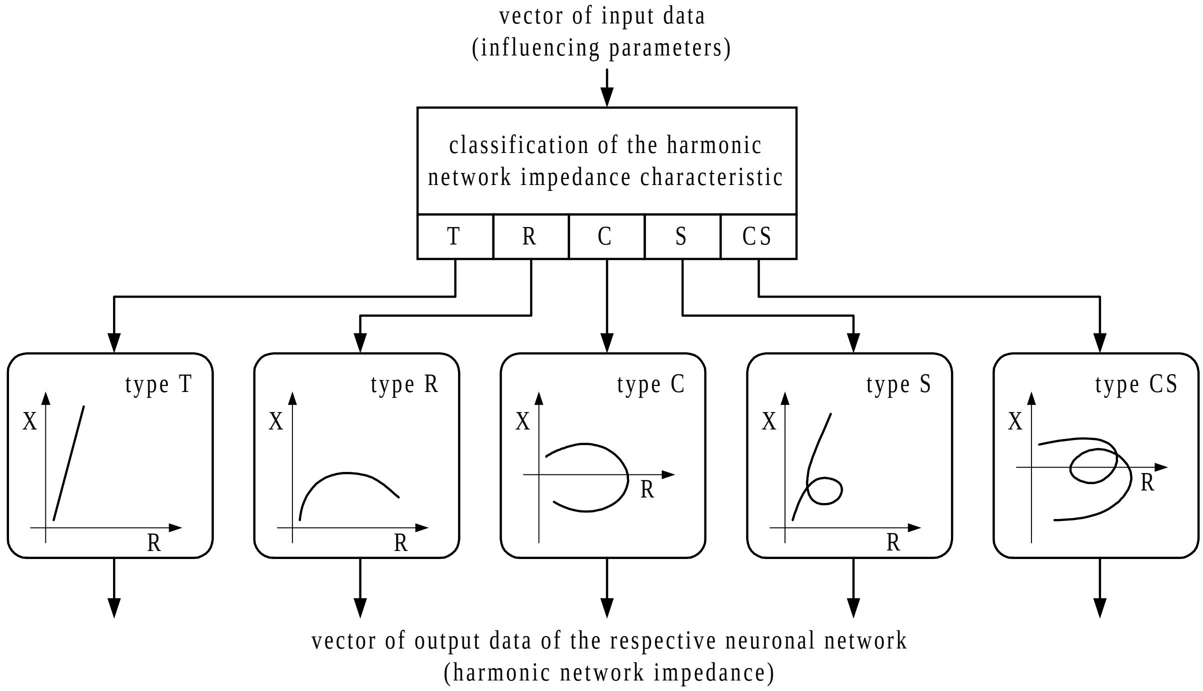


*Figure 9 Principle of the neuronal network*

learning process is very important. Inconsistencies or systematical errors are not recognized by the neuronal network and are handled like valid data during the learning process.

Limits for the usage of the neuronal networks depend on the range of variation directly. If only data of residential area topologies and working days are included into the learning process, forecasting the harmonic network impedance for the weekend in industrial areas is not possible.

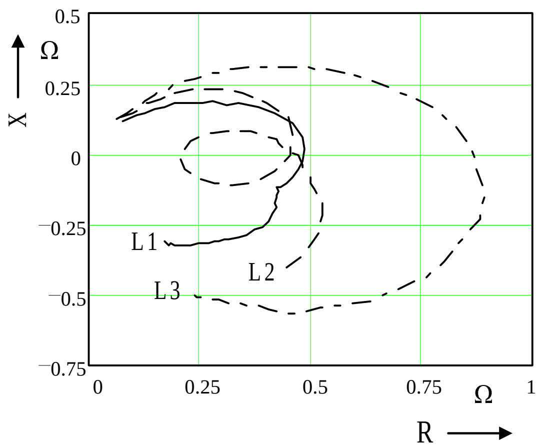


*Figure 10 Different types of harmonic network impedance characteristic for each phase line of one PCC at the same time*

To obtain good learning results for the neuronal networks it is recommended to handle the measurement data of each phase line separately. At PCC's with approximately symmetrical consumer topology, which means similar impedance characteristics for each phase line, it is sufficient to include only one phase line into the learning process. By this an overspezialisation of the neuronal network to one consumer topology can be avoided. However the validity of the input data vector must correspond with the output data of the selected phase line.

If the impedance type differs between the phase lines (fig. 10), the phase line, whose output data vector matches the available input data vector most exactly, has to be chosen. Assuming the causes for the different impedance types are known, another possibility for the handling of such unsymmetrical consumer topologies is the use of different input data vectors for each phase line. In fig. 10 the impedance type CS in phase line L2 is caused by street lighting together with a reactive-power compensation equipment. The different impedance characteristic of the phase lines L1 and L3 results from an unbalanced connection of similar loads.

When the input data vector is only partially known, the algorithm nevertheless returns results. Especially in consumer topologies with a middle or high power consumption the parameters of the network topology (category 3) can be neglected without a significant decrease of accuracy. This feature of the forecasting algorithm further increases it's efficiency.

## EXAMPLE

To verify the presented method, 705 harmonic network impedance characteristics of several low voltage networks were analyzed. The impedances are from residential areas only. These consumer topologies are very complex and difficult to handle with the methods mentioned in fig. 5.

The time period includes working days as well as weekends. The lines of the selected low voltage networks only consist of cables. The measurements took place between June and September. Table 1 summarizes the ranges of input data for the influencing parameters of the consumer and network topologies (categories 1 and 3). Fig. 11 shows the variation of the environmental parameters. The parameters 01 to 05 qualify the percental contribution of each mentioned subcatogory on the PCC's total power consumption. The percentage of electrically supplied equipment for the respective purpose is given for the parameters 07 to 09.

*Table 1 Selected input data ranges for the analyzed consumer and network topologies*

| | influencing parameter | range of values |
|---|---|---|
| 01 | households | 83% to 99% |
| 02 | trade and offices | 0% to 6% |
| 03 | markets | 0% to 9,5% |
| 04 | public buildings | 0% to 4,5% |
| 05 | hotels and restaurants | 0% to 3% |
| 06 | street lighting | 0kW to 14,7kW |
| 07 | off-peak storage heating | 0% |
| 08 | hot water tank | 0% to 80% |
| 09 | electric cooker | 0% to 100% |
| 10 | length of lines | 1500m to 3000m |
| 11 | conductor cross section | 120mm$^2$ to 185mm$^2$ |
| 12 | conductor material | 50% to 100% Al<br>0% to 50% Cu |
| 13 | medium voltage level | 10kV to 20kV |
| 14 | transformer nominal power | 160kVA to 630kVA |
| 15 | transformer utilization | 55% to 85% |

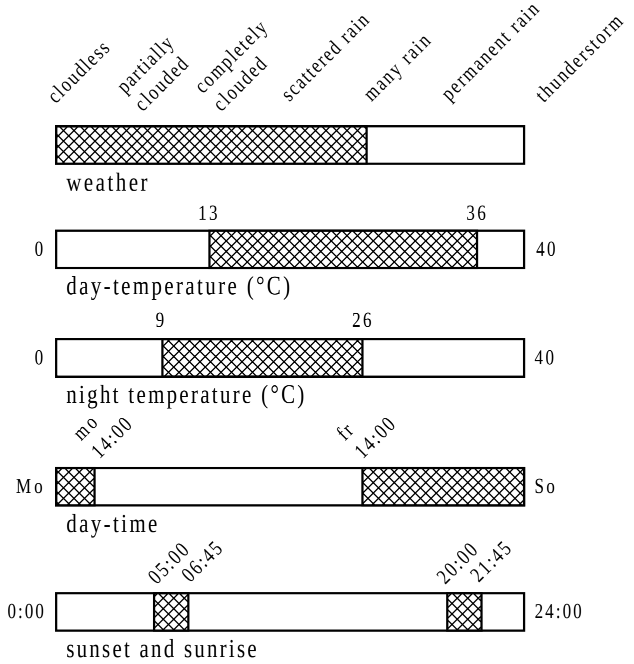


*Figure 11 Range of values for environmental parameters*

The ranges of the values for the three categories of influencing parameters roughly define the limits of the neuronal network. Restricting the data for the learning process to residential areas only causes a certain specialization of the neuronal network, but increases its forecasting precision.

The measured harmonic network impedances are classified according to the 5 specified impedance types. Impedances of type C occur as well as impedances of the types CS and R. After a selection of suitable codebook vectors the learning process for the learning vector quantization is started.

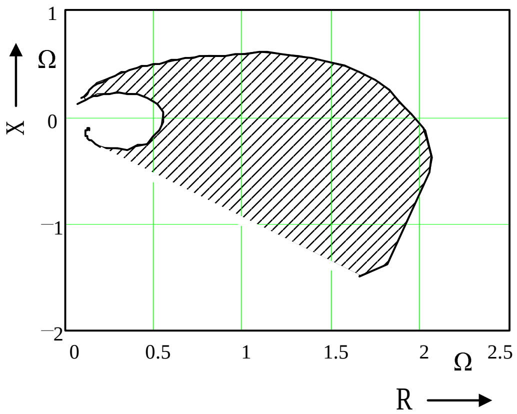


*Figure 12 Range of values for the measured type C impedances*

Taking into account a wide and regular variation of the input and output data, the learning process for each specialized backpropagation network is realized. The range of values for the used impedance characteristics of type C is shown in fig. 12.

Because of random initial weights each learning process results into another minimum of the error surface and accordingly other final weights. That is why a total of 100 learning processes were performed. Finally the best weight configuration is chosen.

To verify the learned neuronal network, the forecasted output data vectors for different input data vectors are compared with the corresponding measurement data (fig. 13 and 14). Especially in the interesting range of the harmonic network impedance characteristic good results are obtained.

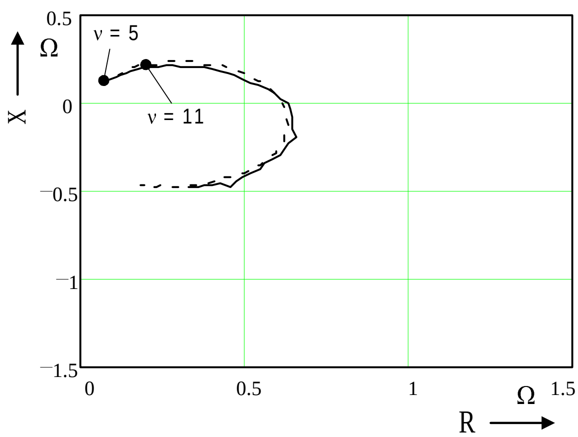


*Figure 13 Forecasting example 1 (forecasting results are dotted)*

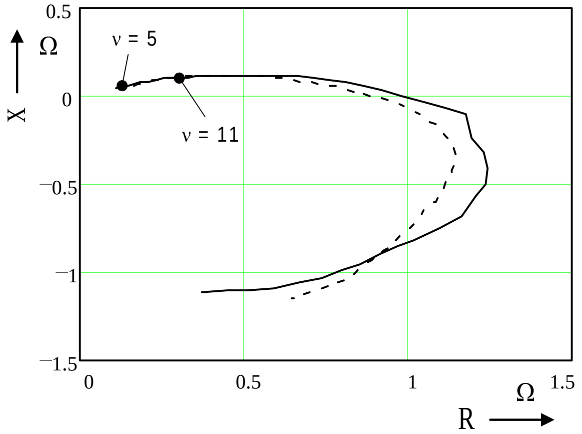


*Figure 14 Forecasting example 2 (forecasting results are dotted)*

## IMPLEMENTATION

The algorithm described above, is part of the software of the measurement system IMEDA (fig. 15) IMEDA is an extensive measurement system and realises the acquisition, archiving, calculation and representation of power quality parameters.

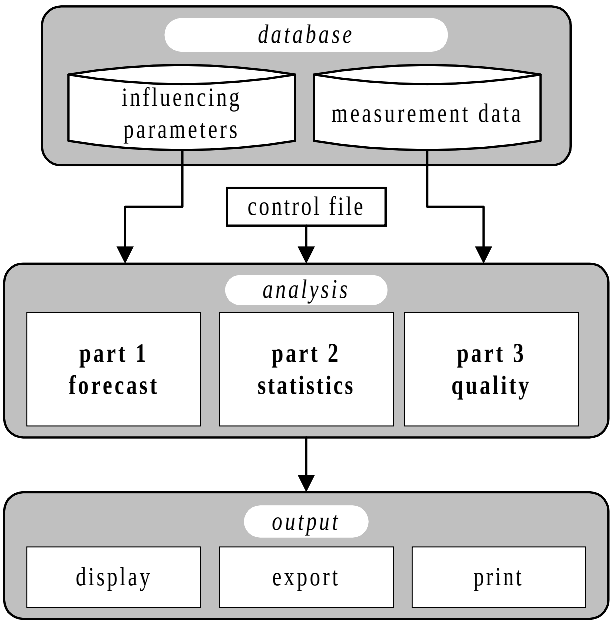


*Fig. 15 IMEDA's analysis software*

The central database stores all data (influencing parameters and measurement data), which are necessary for the learning process as well as for the forecasting process. The setup and control of the program execution is realized by commands provided by a control file. That's why no interaction with the user is needed for different executions of the program. Because of the long calculation times, especially the learning process for the neuronal network benefits from this advantage.

## CONCLUSIONS

The paper describes a method for the calculation of the harmonic network impedance especially for complex consumer topologies in low voltage networks. It is an alternative for conventional network calculation using discrete network elements. Its higher efficiency results from the use of input data, which are easy to obtain. Specializing the neuronal network of a few selected consumer topologies increases the accuracy of the forecasting algorithm. Together with the current harmonics injected at the PCC a calculation of the voltage harmonics is possible during the planning of low voltage networks. Using actual standards, the voltage harmonics planning levels and planning margin can be calculated.

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