DETERMINATION OF SIGNATURES FOR HOUSEHOLD CONSUMERS BASED ON DATA REGISTERED BY SMART METERS

PhD Thesis – Abstract

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PhD field: SYSTEMS ENGINEERING

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In the context of power consumption management, oriented towards its reduction, the PhD thesis proposes, as study object, the identification of the household devices, present in the residential area, based on the voltage and current measurements made by smart meters. It is already known that the amount of consumption reported in residential areas is about 28% of the total power consumption, which includes areas such as agriculture, industry, services, transportation, etc.

The thesis has a linear structure containing 5 chapters with ideas developed gradually. The thesis has 132 pages. It includes, in addition to the 5 chapters, 3 Appendices (A - the support functions associated with the 4 classes: tangent, discontinuous tangent, elliptic and hybrid, B - the values of the solutions' parameters for the case studies presented in chapter 4, C - the MATLAB implementation), 48 figures, 15 tables and 78 references titles, the author of this thesis being the first author of 4 of these titles.

In summary, Chapter 1-INTRODUCTION- discusses the research topic, the goals of the research and thesis objectives. The proposed research topic is to present and argue a new way of obtaining signatures from household consumers. In the context of the thesis, the signature is an analytical expression having the form: $i = f(v,\pi)$ that models the voltage-current dependence for the considered consumer (i - current, v - voltage, - parameters). The goal of the research is to investigate the consumption profile of the residential customer based on the voltage and current recordings made by a smart meter, and to characterize this profile using the signature. The objectives of the thesis are logically deduced from the statement of the topic and the goal of the research. Thus, *the general objective of the thesis* is to investigate the possibility of obtaining signatures for household consumers from measurements made with a low (20Hz) sampling frequency, according to the possibilities of current electrical energy smart meters. *The specific objectives* are: to perform non-invasive experimental investigations, to use as electrical descriptors the voltage-current pairs provided by smart meters (voltage-current trajectory), descriptors that will be the defining element in the calculation of the signature, to define classes of consumers that allow grouping electrical devices according to the voltage-current trajectories.

Chapter 2, entitled "THE PROBLEM OF HOUSEHOLD CONSUMERS' SIGNATURE AND THE FRAMEWORK OF THE RESEARCH TOPIC", is elaborated around a research of references oriented to outline the current state of research in the field of this doctoral thesis and the placement of the thesis topic in this researches. It should be pointed out that the concern with characterising residential power consumption by signatures has begun in 1992 with Hart's article [1]. From the point of view of structuring the information obtained in the reference research , it was considered on the one hand to mention the areas of knowledge involved, primarily from an application perspective [2], and on the other hand to present a set of specific tools. The term "specific tools" includes: the methods applied to determine the signature, the types of descriptors used, and the databases used to define signatures and to test methods.

We mention some examples for each specific instrument:

- Power descriptors: active power [1], reactive power [1], apparent power, power factor, current waveform i(t), voltage waveform v(t) and voltage harmonics, voltage-current trajectory [3]-[12], instantaneous power variation in transient regime, power amplitude variation, duration of transient regime etc.
- Signature determination methods: classical optimization techniques, statistical methods and probabilities, “machine learning” / “pattern recognition” [3]-[12], signal processing techniques, evolutionary algorithms, language processing.
- Databases used: REDD (Reference Power DisaggregationDataset) 16.5 kHz [4], [5], [7], [11], PLAID (Plug-LoadApplianceIdentifcationDataset) 30 kHz [8], [9], [12], [11], WHITED (WorldwideHousehold and Industry Transient Power Dataset) 44.1 kHz, per device, UK-DALE (UK- Domestic Appliance-LevelElectricity) 16 kHz, BLUED (Building-LevelfUlly-labeleddataset for ElectricityDisaggregation) 12 kHz, HELD1 (Home EquipmentLaboratoryDataset) 4 kHz, COOL (Controlled On/Off LoadsLibrary) 100 kHz, ACSF2 (ApplianceConsumptionSignature-Fribourg 2) 1 Hz, 10 Hz, Tracebase 1 Hz.

The chapter ends with the following conclusions: i) the research topic is anchored in the present that is confirmed by the 32 articles quoted, 28 of which correspond to the publication period, namely 2016-2021; ii) the acquisition frequencies used in the research are in the tens of kHz range, the low frequency range not being investigated.

Chapter 3, entitled "SUBSTANTIATION OF METHODOLOGY APPLIED IN THE THESIS", is the essential part of the thesis. The chapter includes the development of a methodology for working towards the proposed objective. At the beginning of the chapter, the working terminology is presented, which includes, on the one hand, established terms from the electrical energy field and, on the other hand, terms specific to the proposed methodology. From the first category we mention: the electrical energy smart meter, seen from the perspective of the minimum functionalities it must provide, the smart grid and the metering infrastructure. The second category includes: multiple consumer (term often used as n-multiple consumer where n is the number of electrical devices it includes), simple consumer signature (analytical expression having the form $i = f(v,\pi)$ approximating the voltage-current trajectory of the simple consumer), n multiple consumer signature (set of analytical expressions having the form $i = f(v,\pi)$ approximating the voltage-current trajectory for an n-multiple consumer), equivalent signature (one or less than n signatures associated with the n-multiple consumer).

As stated, a signature has an expression of the form $i = f(v,\pi)$. Once the expression of the support function f is adopted, the determination of the signature becomes the problem of calculating the parameters. Given the nonlinear forms of the support functions with respect to the parameters, nonlinear regression was used to determine them. In this context f, i and v are called estimator, regressor and predictor, respectively. The problem requires the determination of a set of parameters π such that the function f follows as closely as possible the point cloud resulting from the measurements. Figure 1 shows this aspect: the signature obtained is shown in red and the measurements-related cloud of points is shown in blue.

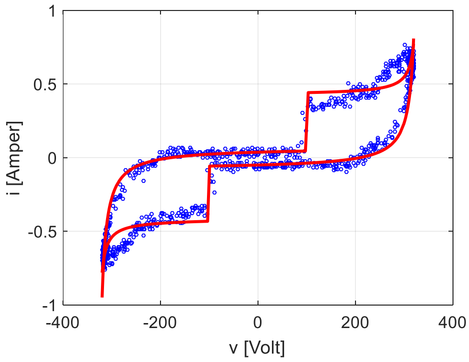


Figure 1. M-point cloud - blue -vs. support function - red - for a discontinuous tangent class consumer.

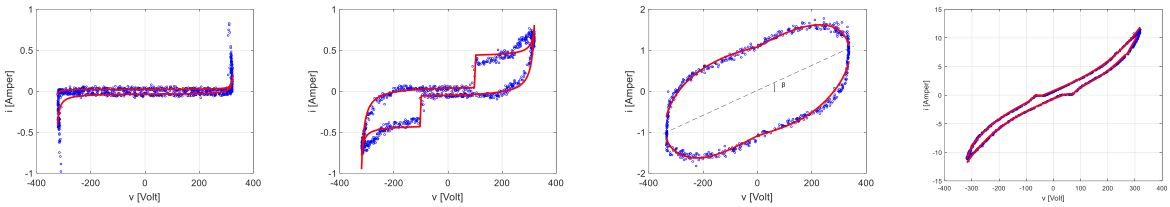
The graph in Figure 1 shows that a signature has two branches, an upward branch and a downward branch. Analytically, this translates into the fact that the estimator f is a union of two expressions corresponding to the two branches.

Regression methods lead to approximation solutions obtained using optimization algorithms. Two algorithms were used in this thesis: the genetic algorithm and the PSO algorithm. In the case of the genetic algorithm (GA), the individual is the set of parameters, and in the case of the PSO algorithm the parameters are the particles in the swarm. The fitness function used by both algorithms is:

$$F_{fitness} = \frac{1}{N_r} \cdot \sum_{j=1}^{N_r} \left[\left| i_j - i(v_j) \right|^{n_j} \cdot \left(1 + 0.2 \cdot e^{-|v_j/V|} \right) \right] .$$

It penalises the sum of the absolute values of the differences between the current $i(v_i)$, measured at a v_i voltage, and the current i_i, calculated for the same voltage, weighted. The expression was obtained empirically based on the study of the behaviour of several types of consumers, finally classified into 4 classes.

The four classes proposed in the thesis - tangent, discontinuous tangent [13], ellipse [14] and hybrid [15] - are plotted in Figure 2.



-a- -b- -c- -d-

Figure 2. Point cloud (blue) versus signature (red): a) tangent class, b) discontinuous tangent class, c) ellipse class, d) hybrid class.

According to the above, the goal of the research undertaken is to propose methods and tools to determine the signature of a n-multiple consumer from a sequence of measurements acquired at a frequency of 20 Hz and having a duration of 51 s. Under these conditions the sequence comprises 1024 pairs of voltage-current samples forming the point cloud on the basis of which the signatures are generated. The set of methods and tools proposed for obtaining the signatures form an aggregate of algorithms which I have called "signature generator". It includes algorithms for allocation (division of the point cloud into subsets corresponding to the two ascending and descending branches, respectively exclusion of points that introduce exaggerated perturbations [13]), for determining the working configuration (operation determined by the type of consumer, respectively by the type of signature to be determined), for determining the membership class, for evaluating the set of parameters π by regression - using GAs or PSOs as a calculation tool-, for signature selection procedures.

Figure 3 shows the measurement scheme used to obtain the signatures. The acquisition of the 1024 voltage-current pairs with a frequency of 20 Hz is performed using a SPTM32 microcontroller found in the smart meter architecture. The acquired data is transmitted to a computer for further processing with the final purpose of generating a signature.

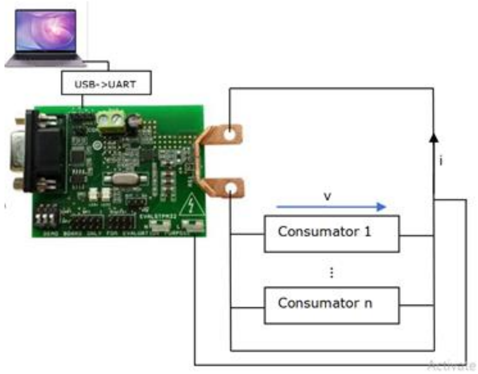


Fig. 3. Measuring scheme.

Figure 4 summarizes the main operations in the signature generator. The figure shows the flowchart of the signature determination method. The sequence of operations depends on the type of consumer, and in the case of consumer n-multiple of the signature variant to be generated (variant 1, variant 2, variant 3) [16].

The signature determination algorithm includes a set of operations depending on the type of consumer: single consumer and multiple consumer, respectively.

- *Operations specific to the Simple Consumer* [15]*:*

  - ✓ determination of Ma, Md sets (allocation algorithm);
  - ✓ choice of work classes (choice of configuration);
  - ✓ determination of the number of independent runs (choice of configuration);
  - ✓ calculation of the fitness and estimation of the parameters associated with the chosen classes by non-linear regression using optimization algorithms, starting from the support functions associated with the classes;
  - ✓ signature selection based on minimum fitness.

- *Multiple consumer specific operations:*

  - ✓ determination of Ma, Md sets (allocation algorithm);
  - ✓ choice of working class combinations (configuration setting);
  - ✓ choice of weighting coefficients (configuration setting);
  - ✓ determination of the number of independent runs (configuration setting)
  - ✓ calculation of: fitness associated with a combination, frequency of occurrence of a combination, parameters associated to a combination, by non-linear regression using optimisation algorithms, starting from the support functions associated to the chosen combinations;
  - ✓ selection of proper or equivalent signatures based on the elements calculated here above or based on minimum fitness only.

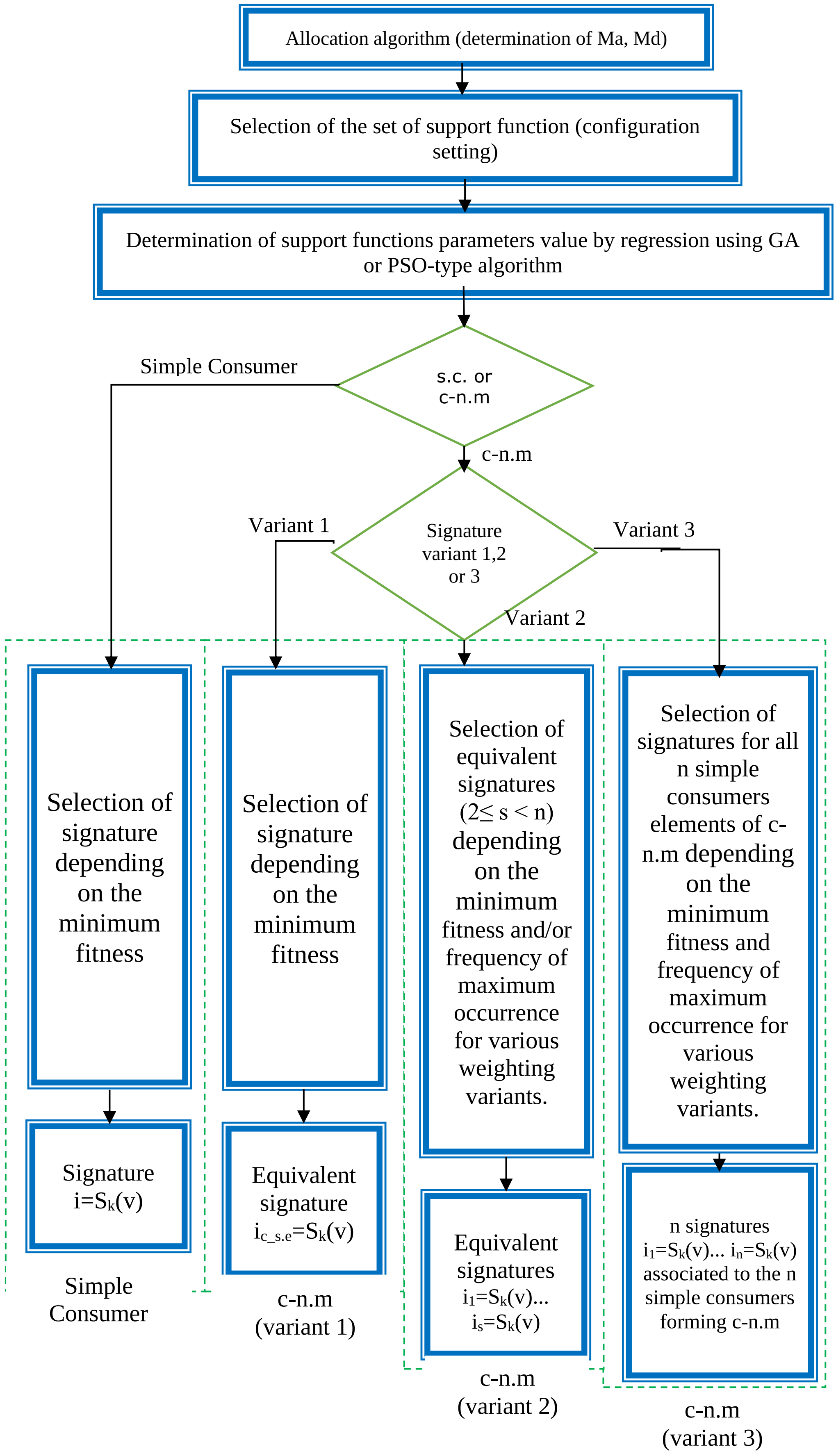


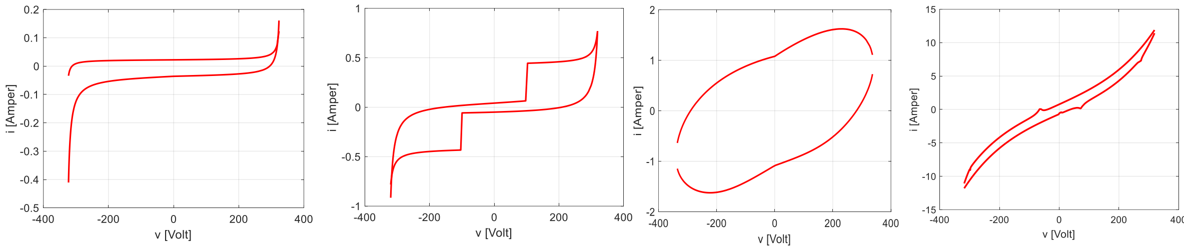
Fig.4 Flowchart of the signature determination method.

Chapter 4 deals with "CASE STUDIES". These validate the methodology proposed in Chapter 3. The case studies cover 4 single consumers and 2 multiple consumers (2-m.c.). The choice of consumers was based on the following criteria:

- ✓ type of consumer (single or multiple),
- ✓ the signature determination algorithm applied in the case of a multiple consumer (3 variants),
- ✓ the class to which the consumer belongs,
- ✓ the percentage represented by the active power of a single consumer of the total active power P consumed by the n-multiple consumer.

Thus, under the heading of "simple consumer" the following were considered: an LCD TV (discontinuous tangent class), a laptop (tangent class), a refrigerator (elliptical class), and a vacuum cleaner (hybrid class), and under the heading of multiple consumers 2 cases were considered: laptop + TV and laptop + vacuum cleaner.

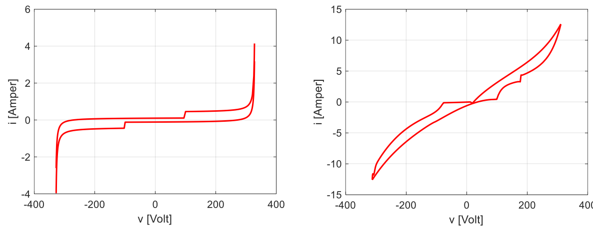
Figures 5 show the signatures of the 4 simple consumers in the following order: a) laptop, b) TV, c) refrigerator, d) vacuum cleaner. They were obtained using a genetic algorithm as an optimization algorithm. When applying the second algorithm, the PSO algorithm, the only difference is that the laptop is placed in the discontinuous tangent class instead of the tangent class. The rest of the results are similar.



-a- -b -c- -d-

Fig. 5 Simple consumer signatures: a) laptop; b) TV; c) refrigerator; d) vacuum cleaner.

For the case of multiple consumer 2, variants 1 and 3 are considered (for 2-m.c., variants 2 and 3 are identical), variants shown in the signature determination flowchart (Fig. 4). In the case of variant 1 an equivalent signature associated with multiple consumer 2 is selected. In Fig. 6 are represented the signatures obtained for the two cases: laptop + TV (left), laptop + vacuum (right). Genetic algorithms were used to calculate the parameters for by regression. Similar results were obtained when applying PSO-type algorithms



-a- -b-

Fig. 6 Equivalent consumer (GA) type signatures: a) laptop+TV b) laptop+vacuum cleaner.

In the case of variant 3 of signature selection for the laptop+TV case, the decomposition of the total current consumed leads to the results from Fig. 7. From the mathematical expressions it can be seen the resulting weights for laptop (0.8) - consumer 1, TV (0.2) - consumer 2, reflecting the difference in power between the two consumers. From the classification point of view of, the laptop is associated with the discontinuous tangent class and the TV with the hybrid class.

Consumer 1:

$$i^1(v) = \begin{cases} 0.8 \cdot S_{2\_a}(v) - upward\ branch \\ 0.8 \cdot S_{2\_d}(v) - downward\ branch \end{cases}$$

Consumer 2

$$i^2(v) = \begin{cases} 0.2 \cdot S_{4\_a}(v) - upward\ branch \\ 0.2 \cdot S_{4\_d}(v) - downward\ branch \end{cases}$$

-a- -b-

Fig. 7. Decomposition of 2-m.c. for laptop+TV: a) laptop signature, b) TV signature.

Similarly, Figure 8 shows the decomposition of the total current consumed in the case of 2-multiple consumer laptop+vacuum cleaner.

Consumer 1:

$$i^1(v) = \begin{cases} 0.985 \cdot S_{4\_a}(v) - upward\ branch \\ 0.985 \cdot S_{4\_d}(v)c - downward\ branch \end{cases}$$

Consumer 2

$$i^2(v) = \begin{cases} 0.015 \cdot S_{4\_a}(v) - upward\ branch \\ 0.015 \cdot S_{3\_d}(v) - downward\ branch \end{cases}$$

-a- -b-

Fig. 8. 2-Multiple consumer type decomposition for laptop+vacuum cleaner: a) laptop signature, b) vacuum cleaner signature.

The graphical representations in Fig. 7 and Fig. 8 were obtained using the genetic algorithm as optimization algorithm.

Comparing the results obtained by using the two optimization algorithms in nonlinear regression, the following conclusions were drawn:

- ✓ In the case of simple consumers both optimization algorithms lead to faithful signatures, the obtained fitness have close values, and in terms of execution times, they are lower in the case of the PSO algorithm.
- ✓ In the case of 2-multiple consumers:
  - In variant 1 of the equivalent simple consumer, the fitness and membership classes of the obtained signatures are similar and the execution times have better values in the case of the PSO-type algorithm.
  - In variant 3:
    - for the laptop+TV consumer, AG provides a global minimum solution - a pair of signatures - with a physical counterpart, whereas the PSO algorithm does not provide such a solution, but this does not exclude local minimum solutions;
    - for the vacuum cleaner + laptop consumer, in the case of adopting

solutions with a physical correspondent, they corresponded for both GA and PSO to local minimum with a low frequency of occurrence;

- the values of the fitness and execution times are lower in this case for the PSO-type algorithm.

Chapter 5, CONCLUSIONS, highlights the author's contributions and possible directions for further research. The ***global contribution*** of the research in this thesis is to demonstrate the possibility of determining signatures of common household consumers using smart meter records, i.e. records made with a low acquisition frequency.

Another important conclusion is that the working methodology proposed in the thesis brings together several ***original procedures***:

- ✓ Selection from the set of measured points the points used to determine the signature, the measured points representing pairs of shape (voltage-current) which, after applying the selection, are considered as the voltage-current trajectory which is in fact the electrical descriptor chosen for the subsequent determination of the signatures;
- ✓ Signature association by estimating parameter values of support functions by nonlinear regression using GA optimization algorithms and PSO algorithms for the following situations:
  - simple consumer signatures determined on the basis of voltage-current trajectories for four consumers of different classes;
  - equivalent signatures for 2-multiple consumers based on common voltage-current trajectories for two cases of 2-multiple consumers;
  - signatures associated with component consumers of 2-multiple consumers based on common voltage-current trajectories;
- ✓ Validation of signature.

In the category of possible directions of research development the thesis mentions:

- ✓ the exploration of the potential of the methodology used in the thesis by extending the number of classes of household consumers and, correspondingly, the type of support functions;
- ✓ the investigation of the influence of increasing the number of measurement points on the quality of the signature by extending the acquisition time of the voltage-current points;
- ✓ the application of the methodology used in the thesis to consumers of higher power than usual domestic ones.

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