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Non-Intrusive Appliance Load Monitoring based on an Optical Sensor

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***Abstract*— -- With the help of the optical sensor described in this paper, a NIALM system can be integrated with little expense in the existing electrical installation of households for analysing and optimising the active electric power consumption. The monitoring system requires as input device the electromechanical three-phase electricity meter (Ferraris meter) installed in the most of the German households. The active power consumption can be measured with time resolution down to second. The measured data constitute the basis for an autonomous NIALM approach which can without manual initialisation phase extract the switching sequence structures of the chief consumer load devices in the household, from the total load trace. The focus of the analysis lies on the automatic controlled on-off consumer loads. The analytical procedure consists of an approach based on certain rules for recognising repetitive patterns. In the decomposition of the total load as a function of time into switching events, simple on-off consumer loads and combinations of these patterns are investigated. The recognised patterns can be stored in a neural network. The network is updated daily and weekly. The results of the analysis are evaluated with regard to the potential for demand optimisation or for controlling the energy consumption of individual electric consumer devices.**

***Index Terms*--fuzzy sets, fuzzy neural networks, fuzzy systems, load management, load modeling, modeling, monitoring, neural networks, optical velocity measurement**

I. Nomenclature

$\{P_i\}$:= series of discrete power values of one day

N_{ADC}:= Number of threshold for analog-digital conversion

S_i := Switching event (in Watt)

$P(S_i)$:= Power value of the i. switch event

$h(S_i)$:= Relative frequency of S_i

N_S := Number of switch events evaluated from the total load of one day

N_C := Number of clusters

C_i := Cluster resp. center of cluster i (in Watt)

N_{C_i} := Number of elements clustered in C_i

V_i := Detected appliance i, (object)

II. Introduction

Non-intrusive appliance load monitoring is since the mid-nineties a mature technique for disaggregating the entire electrical load into the major end uses of domestic homes (cf. [2],[3] and [9]. The evaluation is often based on measuring the reactive and the active power fluctuations on all three phases of the household connection, so that the information with regard to the energy and power consumption can be analysed with a resolution of one second. However, the measuring instrumentation for this costs approximately 1200 Euro per household (cf. [13]). This is too expensive for saturation monitoring in private households. However, the demand data of the households, when gathered with adequate time resolution, entail an enormous potential for numerous services such as demand control, demand optimising, device monitoring and utilisation of dynamic tariff schemes to reduce peak loads. The central problem lies in the low cost acquisition and communication of this data stream with greatest possible time resolution. Low cost systems are required for the data acquisition on the private customer sector, and it must be possible to integrate these systems in the existing household installation with minimised technical and financial effort.

In the Federal German Republic electromechanical three-phase electricity meters, referred to as Ferraris meters in the further course of this paper, are utilised in more than 99% of all households for invoicing the electric power consumption [12]. These meters are read out manually. Measurements or automatic meter reading are possible with these measuring instruments only to a limited extent. For economic reasons (calibration validity, device and maintenance costs) there is no necessity for the local utility network operators in the immediate future for modernising the existing metering system structure.

In order to obviate the expensive replacement of the existing three-phase meters with remote readout digital electricity meters, this paper describes an adaptive system for optical power measurement on the Ferraris meter. Thereafter a NIALM approach is briefly presented for evaluating the acquisitioned meter data. An autonomously functioning system approach is pursued to minimise the need for operator intervention. The goal of the system is to recognise and administer, without manual intervention or external measuring equipment, the major consumer loads which are accessible for optimisation

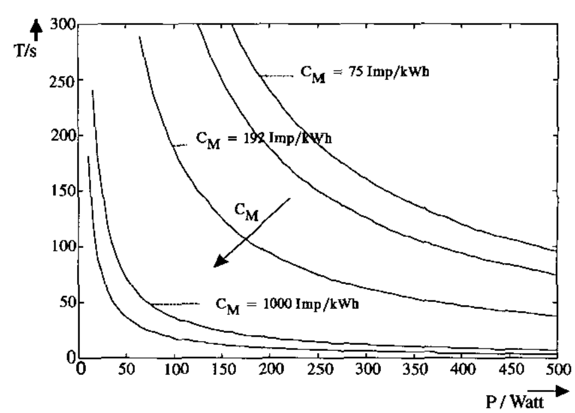

Fig. 1. Dependency of dT and P subject to meter constant C_M.

Ferraris meters are equipped with a mechanical counting mechanism and a rotating meter disc. A red marking is always present on the edge of the meter disc for rough visual recognition, with the unaided eye, of the actual power consumption at any instant and large changes thereof. With optical sensing heads which are available on the market (cf. [14]) the red marking can be detected reliably, so that the number of disc revolutions within a given time of observation can be counted. However, the time taken by the disc for one revolution permits only very coarse time resolution of the fluctuations of the

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mean measured power consumption. The time taken for one revolution of the disc is related to the meter constant and the actual electric power consumption by

$$T_{cycl} = \frac{3,6 \cdot 10^6}{C_M \cdot P} \tag{1}$$

where
C_M is the meter constant expressed as revolutions or pulses per kWh and
P :=is the electric power through the meter.

According to [1] a time resolution of 1s to 15s is necessary for a NIALM solution based on measuring the total active power consumption of a household. The meter constants of modern digital meters can be scaled arbitrarily, but practical utilisation is limited by the S0 pulse interface often used for readout. This interface permits a maximum signal frequency of 16 Hz (cf. [11]). For a theoretically possible peak load of approx. 43 kW in the household, the meter constant must be restricted to approx. 1000 pulses per kWh in order to ensure pulse recognition for true invoicing of consumption with a safety margin in the pulse/pause ratio of the output signal.

Since the analysis of the load fluctuations can only be made on the basis of averaged power values, the time resolution mentioned above and digitising of the power in steps not greater than 50 Watts should be implemented, in order to be able to detect frequently switching smaller consumer loads too.The existing Ferraris meter in the household can be read out inexpensively with high time resolution using the adaptive optical sensor described in the next section. In the most favourable cases, installation is possible without requiring an electrician.

III. New approach to meter reading based on an adaptive optical sensor

Most Ferraris meters have a meter disc with uniform pattern or knurling on the edge. The resulting periodic fluctuations of the light reflection from the disc edge permits optical determination of the rotation speed of such meter discs with very much greater time resolution than is possible by just detecting the red marking. This increased resolution is required in particular when the rated available power is small. The optical sensor is mounted on the meter, thus avoiding physical intervention in the household electrical installation. A CE power outlet is required in the vicinity of the meter only for powering the measuring system. The low-cost Ferraris meter can be retained for consumption invoicing, while it additionally provides high resolution power consumption data for evaluating and optimising the power consumption as a function of time.

A. *Optical methods for measuring the disc rotation speed*

The light beam of an infra-red light source is directed onto the edge of the meter disc. The light beam consists almost entirely of direct radiation. The fraction of scattered light is minimised by the mechanical design of the optical system. The fan-shaped light beam impinging on the meter disc is narrower than the distance between two peaks of the knurled edge of the disc.

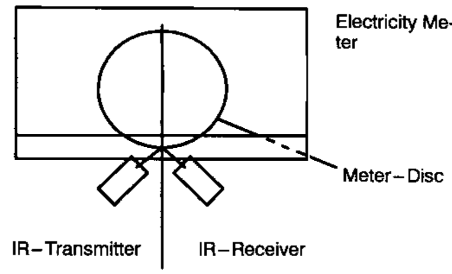

Fig. 2. Schematic construction of the optical sensor and the meter

Only a small fraction of the radiation reflected from the meter disc edge is collected by a conical detector tube which lies in the same plane as the incident light beam and is aligned with the same angle as the incident beam with respect to the perpendicular at the reflection point. The inner coating of the detector tube lets only the directly entering light rays affect the output signal of the I-U amplifier via the phototransistor. This minimises the influence of any disturbing reflections.

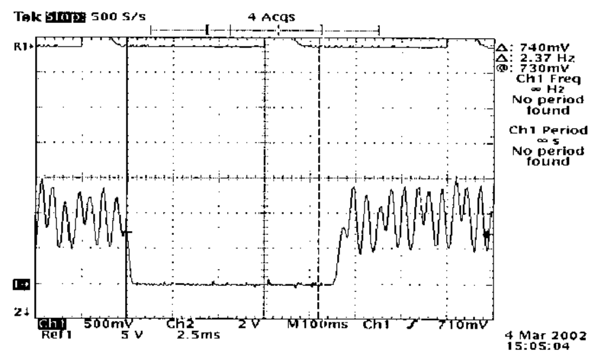

Fig 3: Oscillogram of the sensor signal

The light source is pulsed with 16 kHz so that greater light intensities can be obtained with the IR diode. A further positive side effect of the adopted carrier frequency method is that daylight disturbance is gated out. The electric output signal of the optical receiver circuit is demodulated in analogue mode and contains power-dependent pulse periods with strong amplitude fluctuations. After the analogue signal conditioning, the oscillogram of the output signal is as shown in Fig. 3. The unambiguously detected signal break is the response to the red marking of the meter disc.

B. *Signal conditioning*

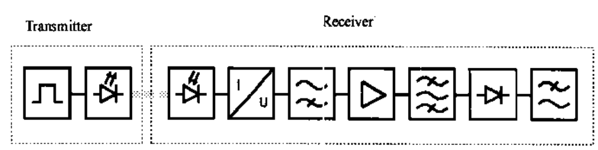

Fig. 4. Block diagram of the sensor signal conditioning chain

The electric signal produced in the receiver is first of all passed through a high pass filter to suppress any remaining daylight disturbance (signal offset). The subsequent bandpass filter selects and amplifies the carrier signal. The signal is then rectified and passed through a low pass filter. The output signal then consists of a pulsating direct voltage with very strongly fluctuating pulse amplitudes. The period length of this alternating signal (Fig. 3) is inversely proportional to the electric power passing through the meter.

C. Evaluation of the spiked signal

The alternating signal with fluctuating amplitudes is transformed to an equivalent TTL signal with the same period. The gate time of the comparator signal is measured with the help of an 8 bit single chip microcontroller. In addition to an external oscillator running with 32.768 kHz, a DCF77 timer chip is provided for exact time-stamping of the measured data. The time measurement is digitised with 16 bits. The power can be calculated with the help of the meter constant and the number of structural transitions on the circumferential edge of the meter disc. The red marking of the meter disc is detected separately and used for online calibration of the measured data. The following relationship exists for the power at any instant:

$$P_i = \beta \frac{1}{Z_i} \tag{2}$$

with

$$\beta = \frac{3,6\cdot 10^6}{C_M N_Z T_{Osz}} \tag{3}$$

$N_Z :=$ Estimated number of structural transitions on the circumferential edge of the disc
$Z_i :=$ Number of pulses from the measurement of one period of the alternating signal from Fig. 3
$f_{Osc} :=$ Frequency of the oscillator

At high rotation speeds of the disc for large power consumption values, not all bright-dark transitions (spikes) can be detected individually, therefore the power value is interpolated for the missing tiepoints. Due to the asynchronous measurement and calculation of the power, two arbitrary adjacent power values P_i and P_{i+k} with k >1during one revolution are not equidistant in time. To obtain time-equidistant sequences of the power value, the missing tiepoints are filled by constant extrapolation.

$$P_i = P_{i+j} \;\; \forall j \in \{1, ..., k-1\} \tag{4}$$

$$E_{cycl} = \frac{3,6\cdot 10^6}{C_M} = const \tag{5}$$

$$C_{kor} = \frac{E_{cycl}}{\sum_{i=1}^{N_Z} P_i \Delta t} \tag{6}$$

The power values for each disc revolution are corrected for one revolution with the help of the fixed energy value to give

$$P_i^* = C_{kor} P_i \quad \forall\, i \in \{k N_Z + 1, .., (k+1) N_Z\} \tag{7}$$

D. Estimate of the measurement error

To estimate the error of the measured data, first of all (2) is differentiated according to Z_i and simplified.

$$\Delta P = \frac{\partial P}{\partial Z_i}\Delta Z_i = -\frac{\beta}{Z_i^2}\Delta Z_i = -\frac{P^2}{\beta}\Delta Z_i \tag{8}$$

Equation 7 first of all shows a quadratic relationship between the influencing variable Z_i and the calculated power. In the consideration of the deviation of the period duration counted with a timer, two influencing variables are taken into account, namely the assumed bit error of a gate time measurement and the time error due to the finite number of digitising steps N_{ADC} of the analogue to digital conversion of the signal.

$$\Delta Z_i = \Delta Z_i^{ADC} + \Delta Z_i^{Bit} \tag{9}$$

Assuming that a maximum signal amplitude corresponding to $N_{ADC}/2$ digitising steps is evaluated, and assuming a bit error of 1 bit for the gate timer measurement with the help of the external oscillator, we get the following error estimate

$$\Delta Z_i^{Bit} = 1. \tag{10}$$

The maximum error for ΔZ_i^{ADC} can be estimated with the help of

$$\Delta Z_i^{ADC} = \frac{\beta}{P}\left(\frac{1}{4} - \frac{1}{2}\pi\, arcsin(1 - \frac{2}{N_{ADC}})\right) \tag{11}$$

assuming a sinusoidal signal waveform. Substituting (9) - (11) in (8) now gives

$$\Delta P = -\left(\gamma_{ADC} P + \gamma_{Bit} P^2\right) \tag{12}$$

It can be assumed that the error distribution is uniformly distributed for both influencing factors, so that a reasonable error estimate can be made with the following values:

$$\gamma_{Bit} = \frac{1}{2\beta} \approx 1,3\cdot 10^{-6}. \tag{13}$$

With $N_{ADC} = 256$ (8 bit ADC) this can be approximated to

$$\gamma_{ADC} \approx 0,01 \tag{14}$$

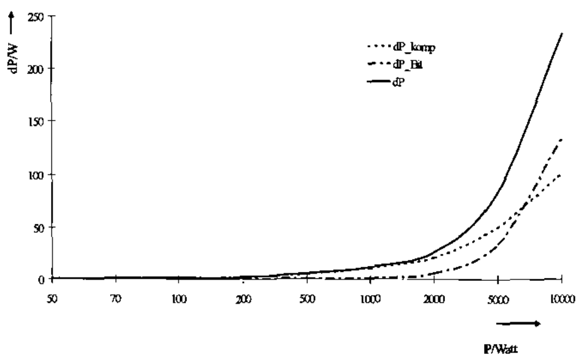

Fig 5. Depiction of the error propagation according to (12)

In Fig. 5 the variation of the power determination error as a function of the actual power according to (12) is plotted with the assumptions from (13) and (14). Large power values can be measured more accurately by detection of the red marking. Particularly at the bottom end of the power range (P < 2000 W) the sensor data are sufficiently accurate for the intended evaluation with high resolution in time.

E. Data conditioning

The power data delivered from the sensor are pre-processed by filters based on certain rules. Undefined break-away readings existing for only very short periods are rejected a priori.Noise superimposed on the signal due to reflection fluctuations on the disc surface must also be rejected by suitable filters. A digital IIR filter is provided for this purpose. The filter operation must be carried out in energy invariant manner, therefore the filter gain must be dynamically adapted in a second step to the data of a complete disc revolution. The digital filter is designed as second order low pass Bessel filter. This prevents overshoots, without unduly damping the steep flanks of real switching events. The difference equation of the algorithm can be taken from the following Z-transmission function:

$$G(z) = K_r \frac{a_0\,(1 + 2z^{-1} + z^{-2})}{1 + \beta_1 z^{-1} + \beta_2 z^{-2}} \tag{15}$$

With the normalised cut-off frequency

$$F_{Gr} = \frac{f_{Gr}}{f_{Ab}} = \frac{1}{30} \tag{16}$$

the calculation of the coefficients of the discrete transmission function gives a_0= 0,014, β_1 = -1,572 und β_2= 0,629.

The filtered set of the power is calculated from the reverse transformation of the following relationship:

$$P^{\#}(z) = K_r\, G(z)\, P^{*}(z) \tag{17}$$

The filtered set can be scaled with K_r in energy-invariant form as performed in (7).

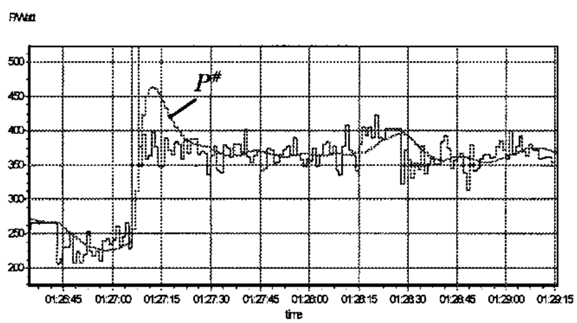

Fig. 6. Time series of $\{P_i^*\}$ and $\{P_i^{\#}\}$, time resolution : 1s

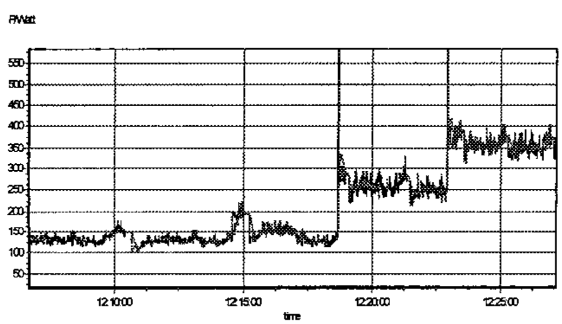

Fig. 7. Switching power steps with a peak (e.g AC-motor)

IV. Autonomous detection of Appliance patterns

A. General goal of the analysis

For the NIALM method a distinction can first of all be made between manual set-up (MS-NIALM) and automatic set-up (AS-NIALM) systems [9]. Autonomous solutions for load recognition analyse the date for recurrent patterns or for patterns already stored in system memory, without requiring any manual intervention by the operator. Thereby the load data of the individual consumer devices are not explicitly measured and entered. This information deficit must be compensated with a high degree of system intelligence. The individual consumer devices are grouped in special classes. Only the electrical parameters of the entire household power consumption are measured. In the solution presented here, the entire active electric power consumption of the household, averaged over one second, is the only input variable for the power consumption investigation. The missing information regarding the reactive power consumption, which would bring a much greater probability of being able to separate the contributions made by the various consumer devices, must be compensated with other derived parameters such as the period duration, the power gradient or the frequency of the switching events. The energy-relevant consumer devices can be monitored with the help of the recognised patterns, and they can be monitored over long periods of time, so that subsequent allocation with the help of a reference database or measured active power consumption of individual consumer devices is possible.

B. Classification of appliances

The typical consumer devices in a household can be roughly classified in 4 categories:

i Permanent consumer devices (constant load)
Consumer devices which are switched on for 24 hours every day, 7 days in the week, with approximately constant active and reactive power consumption.

ii On-off appliances (periodic two-state machines)
Typical switching patterns of appliances with simple two-point control which can be detected in the household mains installation with constant switched-on power consumption, but varying slightly with regard to the duration of the switched-on state and the intervals between successive switched-on states.

iii Finite state machines
Consumer devices which pass through several definite switched states, whereby the complete switching cycle repeats frequently in the daily or weekly cycle of events.

iv Continuously variable consumer devices
Consumer devices with variable power consumption in the switched-on state, without any periodic pattern of the changing switched states. The power consumption and duration of the switched-on state of such consumer devices vary over ranges which do not permit any unambiguous assignment or identification. It is very difficult or impossible to detect consumer devices of this kind with the described measured data, and they do not offer much potential for optimisation.

A further distinction can be made between consumer devices which are controlled (switched) by manual intervention of the operator, and consumer devices which control themselves automatically and autonomously. In this classification it is easier to detect autonomously controlled devices, because their switching cycles are uniformly distributed in time.

TABLE I
CLASSIFICATION OF VARIOUS HOUSEHOLD CONSUMER APPLIANCES

	Active control	Autonomous (automatic) control
Permanent On Appliances	manually switched pumps, air conditioner, etc.	stand–by loads, heating control, aquarium pump
On-Off Appliances	TV, PC-monitor, CD-player, electric lighting, kettle, hair-dryer, electric iron, hoover, toaster, fan heater, kitchen appliances, Rasierer, cooker, stove, boiler	waterheater, fridge, freezer, waterbed, air-conditioner, ventilation, fish tank heating
Finite State Machines (FSM)	washing machine, dishwasher, tumble-drier, PC-printer, electric lawnmower, coffee machine, video, microwave	
Continous variable Appliancess	HIFI-units, lighting with dimmer	

Table I lists the classification of the appliances found most frequently in households. The load analysis methods presented below investigate the load characteristic of the autonomously controlled on-off consumer appliances and autonomous consumer devices with finite status switching sequences (finite state machines). The degree of recognition and the periodic repetitions are here greatest.

C. Extracting Switching Events

The sequence of time-discrete power consumption values $\{P_t\}$ is first of all low-pass filtered. Then the difference set $\{DP_t\}$ is constructed by

$$DP_t = P_t - P_{t-1} \tag{18}$$

The digital low pass filtering converts abrupt power changes to ramps with finite gradient in the signal waveform. With the help of the rule in equation (19) these ramps can be separated into positive and negative switching events. The magnitude of each switching event is given by simple summation of the difference set assigned according to (19)

$$DP_t \in \begin{cases} S_i & \text{if} |DP_t| > \delta \wedge sgn(DP_t) = sgn(DP_{t-1}) \\ S_{i+1} & \text{if} |DP_t| > \delta \wedge sgn(DP_t) \neq sgn(DP_{t-1}) \end{cases} \tag{19}$$

A sequence of detected individual power changes with the same sign is combined as a switching event. The individual switch increments are stored in a dynamic list and bear important information regarding the switch-on characteristic. Many small switching events fall under the measuring system noise and must be sorted out a priori. This is done based on a rule (method III, Fig. 10). The accuracy of the sensor already defines the lower threshold δ for the evaluating algorithm from (19). Thereby the threshold must be dynamically adapted to the power-dependent error of the measurement (cf. Fig. 5).

Since the digital filter according to (15) suppresses considerable amounts of information regarding the switch-on characteristic, a combination of digital filtering and rule-based pre-conditioning of the load data is advisable. Fig. 7 shows the attenuation of a switch-on peak. The filtered rule-based set must be supplemented with this information, because these peaks may contain characteristic information regarding the properties, e.g. of an electric motor.

D. *Clusterung der Daten und bilden typischer Verbraucherstrukturen "Top-Down" Approach*

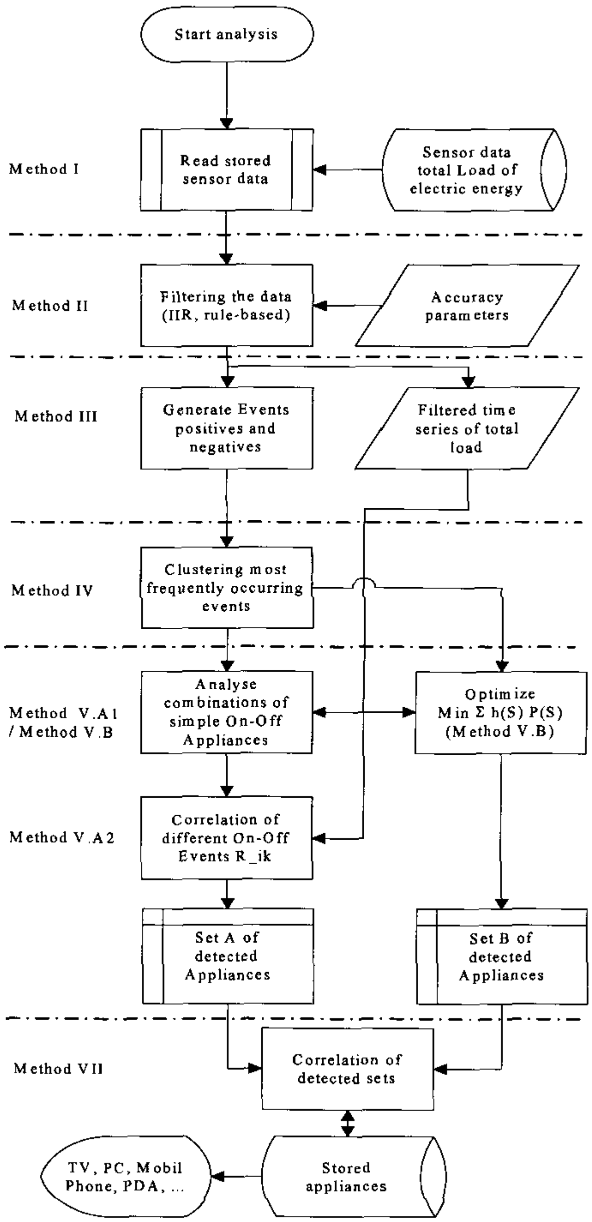

Fig. 10. Overview of the NIALM System

In the method IV the detected positive and negative switching events are clustered according to the ISODATA procedure (cf. [6], [4] and [5]). Thereby the starting values are chosen randomly. The individual clusters are formed with

$$J_S = \underset{S_i}{Min} \sum_{j=1}^{N_S} \mu_{ij} d_i(S_j) \tag{20}$$

and

$$d_i(S_j) = (\overline{S}_i - S_j)^2 \tag{21}$$

whereby

$$\mu_{ij} = \begin{cases} 1 & \textit{für} \quad i : \underset{i}{Min}\, d_i(S_j) \\ 0 & \textit{sonst} \end{cases} \tag{22}$$

For one dimensional clustering of the switching events, the distance between the clusters for two neighbouring clusters can be optimised with the following quality criterion:

$$J_C = \underset{C_i}{Max} \sum_{i=1}^{N_C} 2 \frac{|C_i - C_{i+1}|}{C_i + C_{i+1}} \tag{23}$$

The quality of the entire clustering can be combined in one criterion with the help of suitable weighting by

$$Q = \lambda_C J_C - \lambda_S J_S \rightarrow Max. \tag{24}$$

The number of clusters or the quality of the individual clusters can be adjusted by varying the weighting factors λ_C and λ_S.

The results of the clustering are passed to two parallel utilised methods. Method V.A first of all looks for simple on-off consumer appliances V_i directly in the difference sequence according to Fig. 17, and validates these in real load run.

The concentration centres of the clusters serve for orientation when searching for fitting on-off combinations. Then in method V.A2 the cross-correlation

$$R = \{r_{jk}\} = \begin{cases} \dfrac{1}{N_T} \sum\limits_{t=1}^{N_T} u_{jt}\,, & \textit{für} \quad j = k \\ \dfrac{\sum\limits_{t=1}^{N_T} u_{jt}\, u_{kt}}{\sum\limits_{t=1}^{N_T} u_{kt}} & \textit{für} \quad j \neq k \end{cases} \tag{25}$$

is calculated for found on-off appliances V_i. FSM consumer appliances can be found from lines with coefficients close to 1.

with

N_T := number of data elements in the time series $\{P_t\}$ and

u_{it} := binary state variable, describes the state of an On-Off appliance V_i at time step t, (1 == on, 0 == off)

The respective relative switched-on state times of all found on-off switching event pairs are noted on the diagonal of R. If V_1 and V_2 are two on-off consumer appliances, V_2 appears in connection with V_1 only when r_{12}= 1. Since such ideal cases are very rarely found in practice, the association must be admitted as from a correlation coefficient of $r_{ij} \geq 0.8$.

The method V.B running parallel to V.A evaluates the combinations from the statistical data of the clustering of all switching events from Fig. 13. A further functional

$$J_{FSM} = \underset{\Sigma C_i}{Min} \, |\sum_i h(S_i)\, \overline{P}_{C_i}| \leq \epsilon \tag{26}$$

assesses all combinations of a consumer appliance which may consist of more than 2 switching events (on and off events).

With the relative frequency of the switching events S_i of the cluster C_i

$$h(S_i) = \frac{N_{C_i}}{\sum\limits_{j=1}^{N_C} N_j} \tag{27}$$

and $\overline{P}_{C_i}$, the average of the power of all switching events of the i-th cluster.

With fulfilment of all subsidiary conditions of the real load as a function of time, all possible combinations of finite state machines are generated and archived in set B. The results of the analysis with method V.A (set A) are subsequently superimposed on the results of V.B (set B).

Finally, in method VII all found consumer appliances are compared with the stored consumer appliance patterns and updated. Thereby a back propagation neural network (cf. [7]) is trained with the modiefied properties (number of switching states, the average period time, average energy consumption e.g.) of the detected aplliances.

E. Testresults from real load data

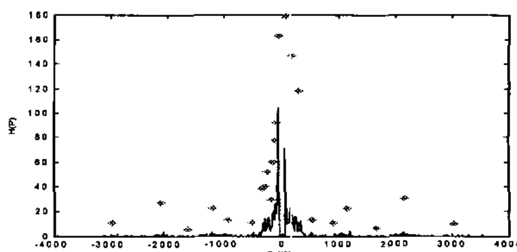

Fig. 11. Clustering of the switching events

The marks in Fig. 11 represent the centers of the calculated clusters. The line describes the graph of $h(S_i)$.

TABLE II
CLUSTER RESULTS FROM FIG. 11

P(S)/W	H(S)	dP(S)/W	h(S)	h(S)P(S)/W
-2975,5	11,0	341,5	0,009	27,8
-2140,1	27,0	114,9	0,023	49,1
-1662,2	6,0	127,8	0,005	8,5
-1211,2	22,0	79,9	0,019	22,6
-939,2	13,0	62,6	0,011	10,4
-531,0	11,0	66,6	0,009	5,0
-346,4	38,0	23,9	0,032	11,2
-291,1	40,0	12,8	0,034	9,9
-240,5	52,0	11,7	0,044	10,6
-194,0	29,0	10,7	0,025	4,8
-153,7	60,0	10,4	0,051	7,8
-116,4	77,0	9,5	0,065	7,6
-82,9	92,0	7,4	0,078	6,5
-57,7	163,0	6,1	0,138	8,0
71,3	179,0	19,4	0,152	10,8
171,7	146,0	32,4	0,124	21,3
291,5	118,0	43,6	0,100	29,2
518,5	13,0	63,3	0,011	5,7
894,6	11,0	93,5	0,009	8,4
1143,6	22,0	76,3	0,019	21,4
1649,2	7,0	108,4	0,006	9,8
2149,0	30,0	116,9	0,025	54,8
3016,1	10,0	241,7	0,008	25,6

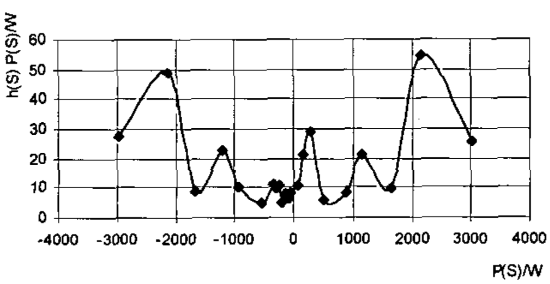

Fig. 12. Evaluation of the clusters according to (26)

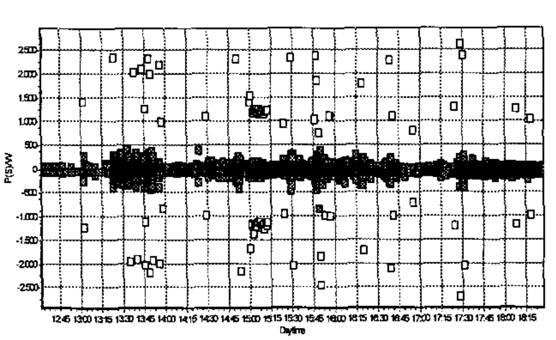

Fig. 13. Evaluated switch events from a period of 6 hours of a day (about 2500 Events), the lighter ones are found On-Off appliances with P > 500 Watts

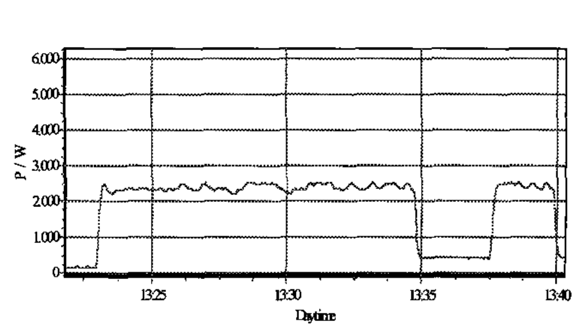

Fig. 14. Extract of the daily household power consumption curve as a function of time

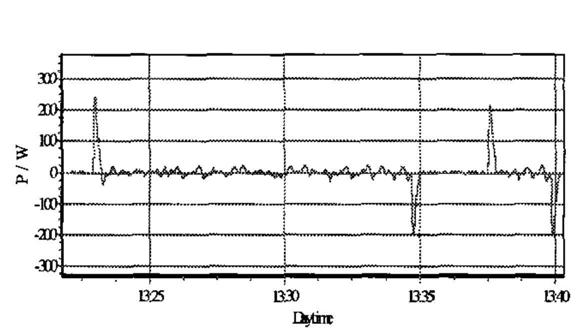

Fig. 15. Difference set $\{DP_t\}$

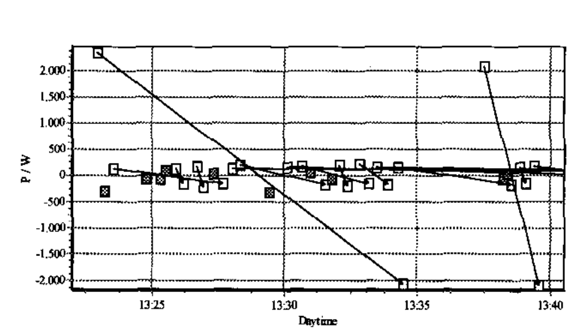

Fig. 16. Evaluation of the On-Off appliances

F. Quality and limitations of the procedure

Simple on-off events as well as combinations of these switching events can be assigned with the help of the introduced procedure. Table 2 shows the clustering results for the switching events on a day for P(S) > 50 W. Clusters with large switch-on power can be combined relatively easily according to Table 2, but the set of switching events with P(S)< 500 W can be associated with recognised appliances only with computer-assisted optimising procedures according to (25) and (26) including the time sequence (cf. Fig. 14, 15 and 16). Fig. 14 shows a section from a real daytime power signal waveform as a function of time, which is mapped in Fig. 14 as difference series and has already been examined in Fig. 16 for simple on-off appliances. The connecting lines designate the associations as recognised appliances.

V. Summary

Optical acquisition of load data provides an inexpensive method for achieving transparency of electric energy demand in private households without installing expensive measuring equipment or new digital electricity meters. The quality of the measured data in close time resolution does not achieve the quality of direct measurement of the active power, but it is an economically efficient compromise with a target price of less than 100 Euro for retrofitting on existing electricity meters. The additional exact detection of the red marking on the meter disc permits measurements of approximately the required quality for true invoicing of electric energy consumed in the household.

For analysing the measured data, an autonomously functioning NIALM approach was devised, consisting of an ISO-DATA clustering method and a combination of rule-based and statistical algorithms. This approach makes possible the autonomous detection of periodic on-off appliances as well as combinations of appliances with finite switching states. The analysing system detects frequently appearing periodic consumer devices such as the refrigerator, or the periodically switching central heating system. Consumer appliances with relatively large switched power, such as the electric cooking stove, or the continuous flow water heater, can also be recognised reliably. Recognition of complex finite state machine appliances only requires computation power which can easily be provided by modern PCs. The timebase of the data analysis is subdivided into day and week periods. The recognised consumer appliance profiles are detected and archived for a week at a time with the help of a neural network. Changes of the consumer appliance patterns are thereby logged explicitly. These patterns contain important information for monitoring the relevant devices. The system concept pursues the implementation of a low cost analysis of the electricity demand in private households, integrated within an intelligent automation of the building without requiring intervention on the part of the operator.

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VII. Biographies

Michael Baranski was born in 1968 in Halle/Westf., Germany. He received the Dipl.-Ing. (FH) in electrotechnics energie technic and Dipl.-Ing. in electrotechnic automatic control in 1995, respectively in 1999. Since 1999 Mr. Baranski is scientific staff member at the institute of power systems of the University of Paderborn. His research interest are systems to analyse and control the total demand of private households integrated in smart home applications. Mr. Baranski is member of VDE

Jürgen Voss (M'1971) was born in 1944 in Riga, Latvia. He received the Ing. degree in information technology and Dipl.-Ing. degree in electrotechnics in 1968, respectively in 1973. In 1977 he received the Dr.-Ing. degree from the Ruhr-University of Bochum in automatic control. Then he was a senior engineer at the Institute of Power Systems at the University of Dortmund. Since 1984 he is a full professor for power systems at the University of Paderbron. His research interests are in power system dynamics, rational power consumption and renewable energies. Dr. Voss is a member of VDE and IEEE.