Nonintrusive Load Detection Algorithm Based on Variations in Power Consumption

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Abstract—**Each electrical appliance has its own pattern of using the electricity. Identifying these patterns can lead to a disaggregation of the entire electricity consumption. This disaggregation, brought to the user, offers a better understanding on how the electricity is consumed inside his home. Also the information obtained from this process brings to the user the power to detect possibilities to reduce its consumption and also its electrical bills, in the context of a world where prices are getting higher each day. This paper presents a new algorithm which detects electrical consumers based on power consumption. The system successfully detects two-state (on-off) and also multi-state devices.**

Keywords-load detection; nonintrusive load monitoring; electric load signature

I. INTRODUCTION

In the current conditions when resources are getting increasingly scarce, leading to an increase of prices charged by utility providers, an important concern is to find solutions to reduce the consumption. Maximizing energy savings is desired given that an increase of the number of consumers and demand of electricity is observed. Also the impact of electricity generation on the environment resulted in finding solutions to improve the management of electricity generation and consumption. In 2008, the European Union set ambitious targets for the year 2020: to reduce the output of greenhouse gases by 20%, to improve energy efficiency by 20% and to increase the percentage of renewable energy by 20% [1].

Substantial resources have been devoted to research and development for energy efficient technologies. However, energy efficiency does not depend only on the technologies used, but also on the choices of the users. Policies to affect these choices mainly focus on price changes (e.g., hourly price shift) and on the information to be delivered (e.g., real-time energy consumption, energy profile, utilities availability).

However, providing users with economic incentive to shift usage to off-peak hours is just one part of the equation. Making the users to understand where the inefficiencies come from, they can act to save energy and money. The information provided by the traditional electricity meters doesn't help the users to find those inefficiencies, since it arrives too late and it comprises only the entire consumption during a long period of time. To overcome this problem, the smart-meter was implemented which offered the user information in real-time about the energy he's using. To better understand where the inefficiencies come from and to find solutions to reduce the consumption, a disaggregation of the consumption by each device is helpful. This can be achieved by using separate metering devices for each appliance or by analyzing the power consumption and detecting those changes which corresponds to a certain device. The second method, called non-intrusive load monitoring (NILM), monitors the whole load at a single point (usually the entrance in household of the electricity network) with one recording device and detects when an appliance switches from one state to another.

The method proposed by G. W. Hart [2] analyses the changes in steady states of normalized active and reactive power consumptions inside a house in order to identify electrical consumers. By plotting these changes into a bi-dimensional plane, clusters of points can be observed which relate with devices turning on/off. This is a simple algorithm which offers good results for appliances with two operating states and represents the base of the future research in consumer detection.

Researchers added different features to be analyzed in order to improve the process of electric load signature identification. For example, the turn-on transients can differ from one type of device to another depending on the physical task they must perform. Devices with similar steady-states variations may have different turn-on transient currents which can be used in the process of identifying the electric load signature [3-5]. The shapes of the transients, which are influenced by the generating mechanism, can be classified according to their parameters: amplitude, duration and time constants. Duration of turn-on transients vary, therefore the algorithms must be implemented so as to be able to adapt to these variations. For example, resistive loads have no turn-on transient or a very short one, while variable-speed motor drives may have turn-on transients of several minutes. Therefore, the system must have capabilities to monitor data at high frequencies over long periods of time. Transient profiles tend generally to maintain their shape even for loads that are using active wave shaping or power factor correction. Most loads have repeatable transient profiles, or at least sections of transient profiles that are repeating. However, analyzing the whole profile of a transient is hard to implement and requires many resources.

Harmonic analysis can also be used to characterize the signature of electric devices [6-9]. While linear loads draw currents of fundamental frequency, non-linear loads draw harmonic currents. Analyzing their amplitudes and the values of harmonic active and reactive power, certain correspondences can be found between a type of device and its harmonic content. Some devices, like an incandescent light bulb and a personal computer, are indistinguishable because they consume essentially the same active and reactive power. They can however be distinguished if a harmonic analysis is performed, when it noticeable that the computer creates a component in the third harmonic signal which is not present in the case of the lightning bulb.

Current waveform, instantaneous admittance waveform, instantaneous power waveform, eigenvalues were also used as features to characterize the electric load signature [10-11]. For inverter-driven devices that frequently change their operational state, radial basis function networks were used to estimate the power consumption [12] and neural networks with higher harmonic spectrum inputs to identify the loads [8,13]. Hidden Markov Model [14] and neural networks combined with support vector machine and Hart's method [15] were also used to identify appliances. Using neural networks the process of device recognition is improved but with high costs regarding the amount of training data necessary to construct the models. An optical sensor attached to a conventional power meter was used to determine the overall active power consumption with a 1 second time resolution [16-18]. The method is based on a Viterbi-type algorithm in order to detect the appliances with multiple states.

Given the particularities of each consumer, the implemented methods are available on certain types of consumers, as it is also observed in [19]. To cover a wider range of consumers, a combination of two or more algorithms can be used [10-11]. This algorithm uses a Committee Decision Mechanism to determine the best result from the combined algorithms. Although an increase in accuracy can be obtained, the algorithm is ambiguous and its computational demand is high.

In this paper, a new and simple algorithm for disaggregating the overall consumption into individual appliances is presented. The algorithm is able to detect the consumers based on changes of active and reactive power consumption. Two new post-processing routines, based on generating combinations of multiple consumers, are proposed in order to improve the consumers' detection. The algorithm is suitable for detection of two-state (on-off) and multi-state consumers.

II. Algorithm Description

The system uses two Hall Effect transducers, LEM LV 25-P respectively LEM HY 5-P, for voltage (U) and current (I) measurement. The transducer outputs are sampled by a NI USB-6211 data acquisition board at a frequency of 50 kHz connected to a personal computer. Continuous data segments of 1 second are acquired and processed in order to determine the values of the real (P) and reactive (Q) powers. During previous research, these values were determined at fixed periods of time: 1 second [2, 16-18], 16 seconds [20-21] or even 15 minutes [22]. Using a fixed period may result in missing some events caused by the consumers switching on or off. Also, if an event occurs during the analyzed data segment, the variations of the current will lead to obtaining average values of active and reactive powers which cannot properly characterize the state before the event occurred. Within the proposed algorithm, a different approach is used to determine the values of the active and reactive powers. Since the voltage can be considered constant (240 V or 120 V), the powers are mainly influenced by the electrical current variations. Using this dependency, an algorithm, which divides the acquired data based on the current variations, was implemented. The RMS values of consecutive periods of the current are compared, and if the variation between them is greater than 10%, a new segment is detected. For each of the detected segments the two powers will be calculated with

$$P_i = mean\left(U_i\left(t\right)\times I_i\left(t\right)\right) \tag{1}$$

$$Q_i = \sqrt{S_i^2 - P_i^2} \tag{2}$$

where S is the apparent power:

$$S_i = U_{RMSi} \times I_{RMSi} \tag{3}$$

and $U_i(t)$ and $I_i(t)$ represents the voltage and current samples of the segment i. To not burden the algorithm with long segments of data, when no variations greater than 10% are detected, the length of the segments won't be larger than 1 second.

With the values of the active power, the segments will be classified as steady-state or variable segments, using a relative threshold. For every two consecutive segments the difference D_i between them is calculated. This difference, if it is greater than 5 W, will be compared with the previous calculated difference D_{i-1}. If the variation between D_i and D_{i-1} is greater than 10% of D_{i-1} (the relative threshold), then a variation is detected; otherwise a constant state is detected. If the constant state lasts more than 5 seconds, than a steady-state segment is detected. The changes of P and Q between two consecutive steady-state segments are calculated and used further by the algorithm to detect the consumers. The algorithm detects consumer's transitions from one state to another and completes its database over time, as new consumers are identified.

Initially the database, which cumulates the consumers' information, doesn't contain any record. Over time, as new consumers are detected, the database is updated with new data. In order to detect a consumer, the algorithm uses the principle that, during an operating cycle (off – on – off), the sum of all variations in power consumption determined by a consumer is zero. This principle can be applied both for consumers with only two states or consumers with multiple states. In Fig. 1, the evolution of active and reactive power consumptions at turning on and off three devices is presented. As it can be seen, the first two (C_1 and C_2) are two-state consumers while the third one (C_3) is a multi-state consumer. Summing the variations measured while passing from one state to another results in a value close to zero.

In Fig. 2, algorithm's block-diagram is presented. It can be observed that the algorithm first performs a segmentation of the acquired data, according to variations of the current. Afterwards each steady-state segment is detected and changes of active (ΔP) and reactive (ΔQ) power are determined. Next, these values are compared with the ones in the data-base in order to check if there is a consumer that presents the same characteristics. If a consumer is found, its state is verified in order to see if is valid. If consumer's previous state is off and next detected state is also off, then the state is invalid (a consumer that is turned off, can't be turned off again) and the algorithm starts checking for possible combinations of previously detected variations. If the state is valid, then the consumer's information is updated and the algorithm continues analyzing the next segment of data.

If no consumer was identified, the current values of ΔP and ΔQ are compared with combinations of previously calculated ΔP and ΔQ values, recorded in two vectors: $\boldsymbol{\Delta P}$ and $\boldsymbol{\Delta Q}$. The sums of these combinations are compared with the current ΔP and ΔQ values to detect if they are within certain thresholds. If the sums are within the predefined thresholds, then a search within the database is performed, in order to identify if there are consumers with the same characteristics. If, after the search, a consumer is found, then its state is checked for validity. If is valid, then consumer's information is updated, otherwise the result of the combination is considered unsuitable to define a consumer, and a new combination will be generated. If, after the search, no consumer is found, then a new consumer is generated and recorded in the database. The variations of the valid consumers are deleted from ΔP and ΔQ in order to not interfere next time a combination will be generated.

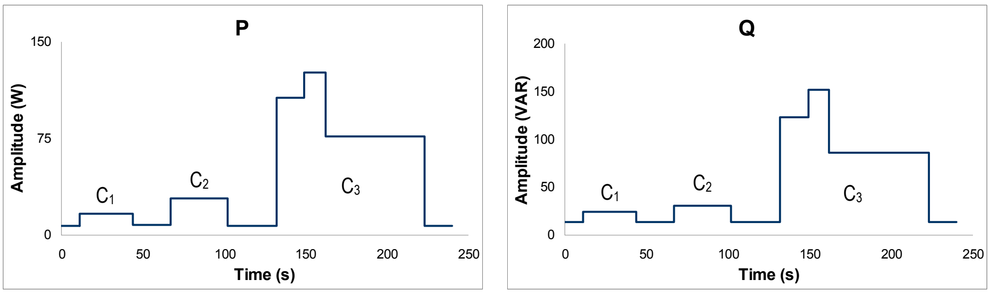
After all combinations were verified, the algorithm performs two routines: *Check Multiple Cons* and *Check ZeroCons.* The first routine checks if the current values of ΔP and ΔQ are the result of turning on/off multiple consumers at the same time. If ΔP and ΔQ are negative, the routine search combinations between consumers that are marked as turned on, else if ΔP and ΔQ are positive, the routine search combinations between the identified consumers. The sum of the combination has to be equal or within predefined thresholds of current ΔP and ΔQ values. If a combination of consumers is found, their information is updated according with the values of ΔP and ΔQ.

Check ZeroCons is performed only when the power consumption reaches a level recorded initially when no consumers are turned on. This routine helps identify those variations which were wrongfully attributed to a certain consumer. It is possible that a multi-state consumer have a variation which is identically with the one of a two-state consumer. In this case the two-state consumer is identified and, since the corresponding values of ΔP and ΔQ weren't recorded into $\boldsymbol{\Delta P}$ and $\boldsymbol{\Delta Q}$ vectors, the multi-state consumer will be missed. When power consumption reaches a level corresponding with no consumers being turned on, the routine checks which consumer is marked as turned on and moves its ΔP and ΔQ values into $\boldsymbol{\Delta P}$ and $\boldsymbol{\Delta Q}$ vectors. With these new vectors, combinations whose sum is zero or within predefined thresholds are searched. As result, the missing consumer won't be missed again and the consumers mistakenly detected will be marked with the correct state. Within this routine, a problem arose in establishing the power level when no consumer is turned on. A consumer when is plugged into the outlet, even if it isn't turned on, because of its impedance, it consume a small amount of power, called phantom load. This isn't a problem for a single consumer, but when multiple consumers are plugged in, the total amount can reach a considerable value. Therefore the power level corresponding to no consumer being turned on will be updated each time no consumer is marked as being turned on and $\boldsymbol{\Delta P}$ and $\boldsymbol{\Delta Q}$ have no elements.

III. Experimental Results

In Fig. 3, the steady-state segments of active and reactive power consumption, generated by turning on and off 4 different consumers (PC, LCD monitor, oscilloscope and incandescent light bulb), are presented. It can be seen that the first and the last steady-state segments are at the same level, which corresponds with the situation of none of the consumers being turned on. For a better explanation of how the algorithm works, the ΔP and ΔQ values are presented in Table 1.

The algorithm, as it acquires new segments of data, detects when steady-states occur and calculate ΔP and ΔQ values. First values represent the phantom loads corresponding to the consumers being plugged in.



a. b.

Figure 1. Active (a) and reactive (b) power variations for three devices (C_1 – oscilloscope, C_2 – LCD monitor, C_3 – PC).

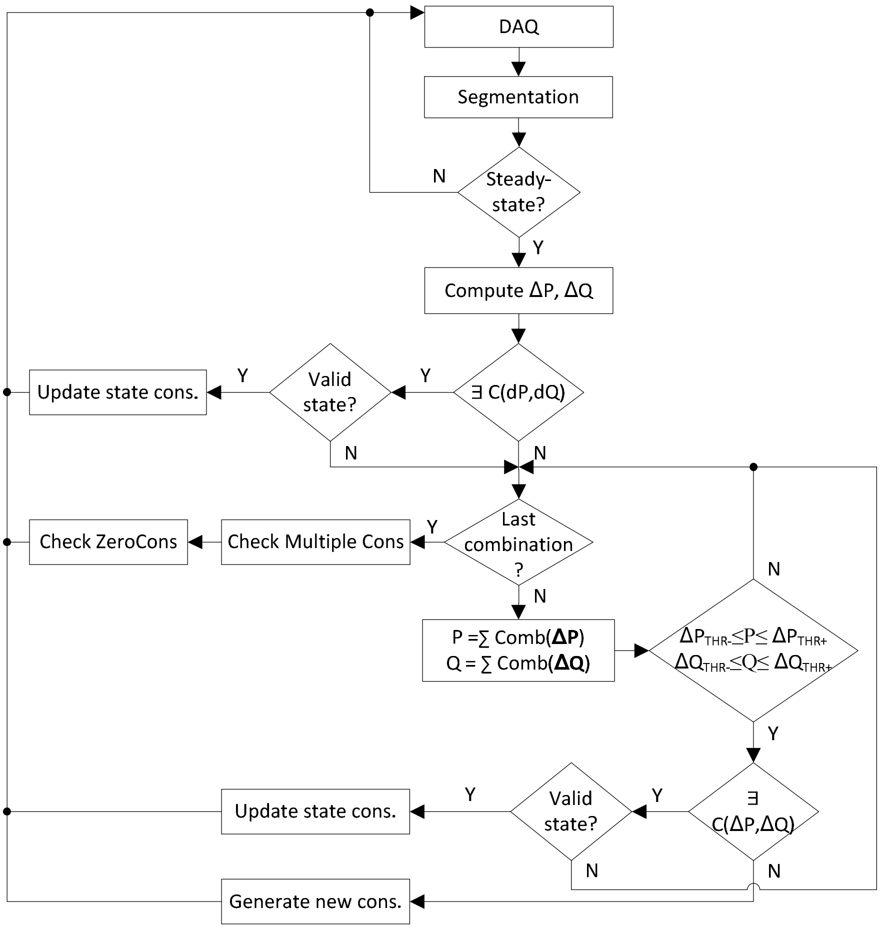
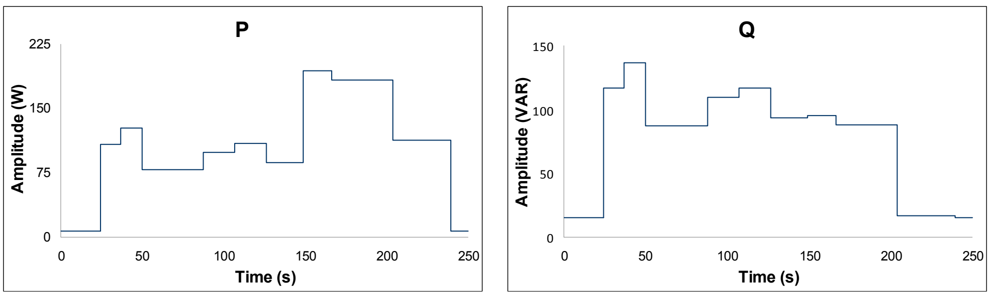


Figure 2. Block-diagram of the implemented algorithm.

As new values are obtained, the algorithm searches combinations whose sum is within predefined thresholds of ΔP and ΔQ values, which were set to 90% and 110% of ΔP and ΔQ. For variations smaller than 10 W or 10 VAR, the thresholds are increased with 1 W and 1 VAR. These values were added because the thresholds for small variations leave a small margin of error, and therefore some transitions of a consumer from one state to another can be misinterpreted. For example, an incandescent light bulb can determine a variation of 0.98 VAR when turned on and -1.32 VAR when turned off. The difference between the two values is 0.4 VAR, which is 30% of -1.32 VAR, greater than the 10% threshold.

With the values from Table 1 the algorithm doesn't detect any consumer until it reaches time 126, when it finds the first consumer (C_1) having the following characteristics: ΔP = 21.48 W and ΔQ = 22.88 VAR. The next detected consumers are C_2 at t = 166 with ΔP = 10.55 W and ΔQ = 7.65 VAR, C_3 at t = 204 with ΔP = 120.13 W and ΔQ = 121.35 VAR and C_4 at t = 240 with ΔP = 106.58 W and ΔQ = 1.15 VAR.



a.

b.

Figure 3. Variations of power consumption generated by 4 consumers: a. variations of active power, b. variations of reactive power.

TABLE I. VARIATIONS OF POWER CONSUMPTION GENERATED BY 4 CONSUMERS

Time (s)	0	24	37	50	88	107	126	149	166	204	240
ΔP (W)	7.14	101.48	18.65	-49.75	20.44	10.22	-22.51	106.69	-10.89	-70.24	-106.48
ΔQ (VAR)	15.33	100.91	20.45	-49.68	22.13	7.17	-23.63	0.98	-8.14	-71.10	-1.32

IV. CONCLUSIONS

In this paper, a simple algorithm that successfully detects two-state and multi-states consumers based on the changes in active and reactive powers between two steady states was presented. The efficiency of this algorithm depends largely on the accuracy of the process of obtaining the power changes. For this purpose, a new method of segmenting the data, according to current variations, was implemented. The algorithm will closely follow each variation in power consumption and will properly characterize each steady-state. This way, each time an event occurs, the recorded power changes will present only variations of small magnitude which will not influence the detection process.

Each consumer, during an operating cycle, determines changes of active and reactive power whose sum is equal to zero. Using this principle, an algorithm was implemented to disaggregate the whole consumption into separate loads.

Two new routines were implemented to obtain an increase in consumer detection, namely *Check Multiple Cons* and *Check ZeroCons*. The first routine has the role to find, if for a certain detected variation, different combinations of consumers can be found. This way, consumers that are turning on/off at the same time won't be missed.

The second routine has the role to detect those states whose power levels correspond to no consumer being turned on and check if there are consumers marked as being turned on. In this case, all the variations corresponding to the on consumers are brought to $\boldsymbol{\Delta P}$ and $\boldsymbol{\Delta Q}$ and different combinations are generated to detect which consumers generated the respective variations.

Considering the experimental results, it can be concluded that the presented algorithm, with the new method of tracking the power changes and the two routines, can detect on-off and multi-state consumers and covers most of the situations that may encounter in consumer detection.

REFERENCES

[1] World Business Council for Sustainable Development, "Energy efficiency in buildings: Business realities and opportunities", Technical report, 2008.

[2] G. W. Hart, "Nonintrusive appliance load monitoring", Proceedings of the IEEE, vol. 80, pp. 1870-1891, 1992.

[3] L. K. Norford, S. B. Leeb, "Non-intrusive electrical load monitoring in commercial buildings based on steady-state and transient load-detection algorithms", Energy and Buildings, vol. 24, pp. 51-64, 1996.

[4] U. A. Khan, S. B. Leeb, M. C. Lee, "A multiprocessor for transient event detection", IEEE Transactions on Power Delivery, vol. 12, pp. 51-60, 1997.

[5] H. H. Chang, C. L. Lin, J. K. Lee, "Load Identification in Nonintrusive Load Monitoring Using Steady-State and Turn-on Transient Energy Algorithms", in Proceeding of the 2010 14th International Conference on Computer Supported Cooperative Work in Design, pp. 27-32, 2010.

[6] A. I. Cole, A. Albicki, "Nonintrusive identification of electrical loads in a three-phase environment based on harmonic content", in Proceedings 2000 IEEE instrumentation and measurement technology conference, pp. 24-29.

[7] K. D. Lee, S. B. Leeb, L. K. Norford, P. R. Armstrong, J. Holloway, S. R. Shaw, "Estimation of variable-speed-drive power consumption from harmonic content", IEEE Transactions on Energy Conversion, vol. 20, pp. 566–74, 2005.

[8] D. Srinivasan, W. S. Ng, A. C. Liew, "Neural-network-based signature recognition for harmonic source identification", IEEE Transactions on Power Delivery, vol. 21, pp. 398-405, 2006.

[9] C. Laughman, K. Lee, R. Cox, S. Shaw, S. Leeb, L. Norford, P. Armstrong, "Power Signature Analysis", IEEE Power and Energy Magazine, vol. 1, pp. 56-63, 2003.

[10] J. Liang, S. K. K. Ng, G. Kendall, J. W. M. Cheng, "Load Signature Study-Part I: Basic Concept, Structure, and Methodology", IEEE Transactions on Power Delivery, vol. 25, pp. 551-560, 2010.

[11] J. Liang, S. K. K. Ng, G. Kendall, J. W. M. Cheng, "Load Signature Study-Part II: Disaggregation, Framework, Simulation, and Applications", IEEE Transactions on Power Delivery, vol. 25, pp. 561-569, 2010.

[12] H. Murata, T. Onoda, "Estimation of power consumption for household electric appliances", Proceedings of the 9th International Conference on Neural Information Processing, vol. 5, pp. 2299-2303, 2002.

[13] Y. Katsuhisa, N. Yukio, A. Yoshimitsu, "Non-Intrusive Appliances Load Monitoring System Using Neural Networks", Transactions of the Institute of Electrical Engineers of Japan C, vol. 122, pp. 1351–1259, 2002.

[14] N. Hisahide, I. Koichi, S. Tatsuya, "Non-Intrusive Appliances Load Monitoring System Using Hidden Markov Model", Transactions of the Institute of Electrical Engineers of Japan B, vol. 126, pp. 1223-1229, 2006.

[15] M. Hakase, O. Takashi, Y. Katsuhisa, N. Yukio, K. Shuhei, "Non-Intrusive Appliances Load Monitoring System. Application experiment to real household", Transactions of the Institute of Electrical Engineers of Japan C, vol. 124, pp. 1874-1880, 2004.

[16] M. Baranski, J. Voss, "Non-Intrusive Appliance Load Monitoring Based on an Optical Sensor", EEE Power Tech Conference, Bologna, 2003.

[17] M. Baranski, J. Voss, "Genetic Algorithm for Pattern Detection in NIALM Systems", IEEE International Conference on Systems, Man and Cybernetics, pp. 3462-3468, 2004.

[18] M. Baranski, J. Voss, "Detecting Patterns of Appliances from Total Load Data Using a Dynamic Programming Approach", Fourth IEEE International Conference on Data Mining (ICDM'04), 2004

[19] M. Zeifman, K. Roth, "Nonintrusive Appliance Load Monitoring: Review and Outlook", IEEE Transactions on Consumer Electronics, vol. 57, pp 76-84, 2011.

[20] L. Farinaccio, R. Zmeureanu, "Using a pattern recognition approach to disaggregate the total electricity consumption in a house into the major end-uses", Energy and Buildings, vol. 30, pp. 245-259, 1999.

[21] M. L. Marceau, R. Zmeureanu., "Nonintrusive Load Disaggregation Computer Program to Estimate the Energy Consumption of Major End Uses in Residential Buildings", Energy Conversion & Management, vol. 41, pp. 1389-1403, 2000.

[22] J. Powers, B. Margossian, B. Smith, "Using a Rule-Based Algorithm to Disaggregate End-Use Load Profiles from Premise-Level Data", IEEE Computer Applications in Power, pp. 42-47, 1991.