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Real-Time Event-Based Energy Metering

Mikhail Simonov, *Member, IEEE*, Gianfranco Chicco, *Senior Member, IEEE*, and Gianluca Zanetto

Abstract — **Real-time knowledge about the energy being exchanged sustains energy efficiency applications and services. The event-based data-saving approach to the measurements of electric energy has emerged recently with conceptual and practical implications, also thanks to the manufacturing of a new technological solution. This paper explains the fundamental underlying concepts that have led to these improvements through real-case examples. This work borrows from ontology the distinction between the concepts of endurants and perdurants, associating these concepts to the quantities involved in the energy metering process. In the new event-based computational framework, energy metering is interpreted by detecting average power and accumulated energy variations, as well as highlighting the importance of the information provided by the rate of change of energy and by the rate of events gathered from meters.**

Index Terms— **Energy, Measurements, Data analysis, Event-based data monitoring, Metering.**

I. Introduction

In the context of rapidly evolving digital information and communication technologies and lower costs of electronic programmable devices, energy metering is living a new era. The traditional approach to energy metering is based on gathering data at regular time intervals. Recently, some researchers applied alternative approaches that allowed reducing the amounts of data exchanged between measurement agents. Load pattern analysis' researchers [1] found that for most of the time the patterns remain almost constant. Thereby, until no significant changes occur, there is no need to send information [2]. This logic is based on the detection of *events* to determine the timings for data reading, changing the way data are gathered from regular timing to non-regular timing. The criterion for determining the occurrence of significant changes was then extended to the case in which the pattern has slow but continuous variations. A two-threshold system was proposed in [3] in order to maintain consistency with the present legacy depending on the timer-based regular data gathering. The characteristics of Timer-Based Metering (shortly TBM) and Event-Based Metering (shortly EBM) were discussed in [4] in terms of data representation based on concepts of *accumulated energy* and *accumulated energy variations*. In the context of new digital EBM energy meters fabricated in 2015 [5], more energy users may be included in the real-time scenario.

This paper discusses the effectiveness of the domain-specific framework for real-time energy metering upon events. This framework is rather different with respect to the way events are used in other research fields. For example, in digital signal processing events are considered to generate non-uniform sampling in applications with variable frequency content, with the objective to avoid avoiding high-frequency sampling and thus saving power in analog-to-digital converters and digital signal processors [6]. In these applications, the reconstruction of the signal is aimed at reproducing its shape by using interpolation or approximation methods [7]. In power quality monitoring, the detection of an event is typically used to record the waveforms of some relevant quantities (e.g., voltages at the electrical network nodes) only during the event, avoiding the recording of the whole data stream during normal operation [8]. The recorded data during the events are used to try and identify the type of event occurred and its characteristics in a post-processing phase [9]. In event-driven programming [10], the events correspond to conditions (e.g., end of file, limits reached on variables) or external operations (e.g., pressing buttons, mouse movements) that determine a change in the execution of the program. The event-driven approach has been used in circuit and system design, for example in clock-less applications with signal-dependent sampling rate and adaptive resolution [11], or in frame-free event-driven vision systems, in which each pixel decides autonomously when to send its address out in an asynchronous way [12]. In sensors applications, the send-on-delta reporting scheme presented in [13] determines an event when the monitored quantity changes more than a specified threshold (delta) with respect to the value identified for the last event. This leads to asynchronous timing of the reported events. In hybrid control systems, used in different applications including manufacturing processes [14], air traffic management, engine control, embedded control, robotics and others [15], time-driven and event-driven dynamics are interacting, with discrete events acting as trigger mechanisms managed by the controller [16]. Further contents on event-based control and signal processing are discussed in [17].

The main difference between the TBM and the EBM approaches depends on the nature itself of the quantity represented – *energy*. While in the classical event-based approach the quantity of interest represents the event itself happening in the system, without the need of reconstructing the history of the previous evolution of the system, energy metering needs to maintain the information on the previous evolution to avoid losing any Amount of Energy (shortly AoE) used in the system. In this sense, in many cases of the classical

M. Simonov is with Istituto Superiore Mario Boella, via P.C. Boggio, 61, 10138 Torino, Italy (e-mail simonov@ismb.it).
G. Chicco is with Politecnico di Torino, Energy Department, Power and Energy Systems group, Corso Duca degli Abruzzi, 24, 10129 Torino, Italy (e-mail gianfranco.chicco@polito.it).
G. Zanetto is with TeamWare S.r.L., Via Pindaro, 19, 20128 Milano, Italy (e-mail gianluca.zanetto@teamware.it).

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event-based approach (markedly in signal processing) the basic concept is the one of *sampling,* aimed at reconstructing in the best way possible the detailed evolution of a signal in the time domain, even without calculating the energy associated with the signal. Conversely, in energy engineering applications the key aspect is the conservation of the energy represented, regardless of the detailed reproduction of the evolution in time of the patterns referring to the quantities determining that energy. The notion of sampling being replaced by the averaging time step [4] is formally made unnecessary because the integral quantity allows deriving the average power *by computation*. Hence, EBM becomes an application retaining its own specificity with respect to other event-driven applications. This paper discusses these concepts, highlighting their peculiarity and meaning in the energy metering process, resorting to real-case examples.

The next sections of this paper are structured as follows. Section II introduces the fundamental concepts. Section III deals with relevant quantities and event generators used in the novel computational framework, also interpreted in domain-specific terms of accumulated energy variations. Section IV shows how to gain insights from application cases. The last section contains the concluding remarks.

II. Fundamental Concepts

A. Timing aspects

In order to describe the timings used to characterize the energy metering process, let us define the following entries:

- *Elementary time interval*: is the fastest time interval of *duration* τ used to calculate integral values such as energy, average power, and other RMS values. The elementary time interval represents the reference time step for the timeline indicating the evolution of the natural time t.
- *Time interval* Δt: an ordered sequence of a defined number of elementary time intervals associated with the representation of a specific pattern.
- *Time period* T: a succession of time intervals (even with different duration); the duration T of the time period is a multiple of τ.
- *Time tag*: a time instant at which a given elementary time interval starts. Time tags (or time stamps) provide the link between the discrete sequence of elementary time intervals t_k, scan by the subscript k, and the natural time t.

A discretized framework referring to integral values imposes that anything happens inside an elementary time interval cannot be identified. All the quantities within any elementary time interval are represented as constants, leading to a *stair-wise* representation of the corresponding patterns. The representation with constant *average power* referring to a time step of certain duration implies that no pattern of instantaneous powers can be identified *inside* that time step.

In the *timer-based* approach, the energy *measurement process* always generates a stream of observations flowing at *discrete* and constant rate of time [18], e.g., the limitless ordered sequence of time tagged terms $\{t_k, \mathbf{x}_k\!=\!\mathbf{x}([t_k\text{-}\tau,\ t_k])\}$, where t_k is the time stamp associated with the data, and $\mathbf{x}_k$ is the measured quantity encoding the *self-information*. The left hand-side of Fig. 1 represents the time intervals being spaced uniformly, that is, $\Delta t_{i+1} = \Delta t$. Fig. 1 also indicates the distinction of the time-related indications between endurants and perdurants explained in Section II.B.

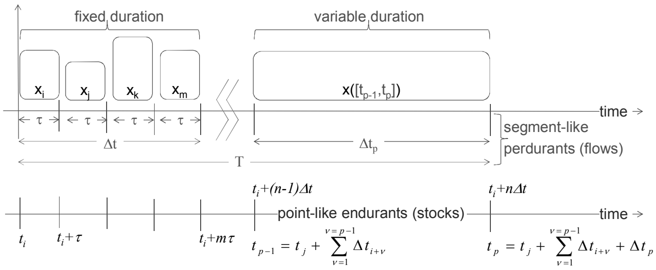

Fig. 1. Representation of the timings.

In the *event-based* approach, the measurement process generates an *unevenly spaced sequence* of terms. The data abstraction remains unchanged, but the information is not encoded in single variables, but inside the pairs of attributes referring to the successive time instants t_{j-1} and t_j. The duration $\Delta t_j = t_j - t_{j-1}$ is a multiple of τ and depends on *how* the pattern has evolved in the sequence of elementary time intervals. By using *chunks*, namely, fragments of information being included in a set of data in order to communicate the characteristics of the processes lasting in time, the succession of information identifying the energy metering process is represented by a chained list of chunks [19].

B. Endurants and Perdurants

To understand the semantics of the event-based data objects, let us consider two kinds of very different items: the *instants* and the *durations*. Geometrically speaking, those entities are *point*-like and *segment*-like, respectively. A categorization of the entities comes from ontology, which considers the nature of being, as well as the categories of being and their relations [20]. In *ontology* terms [21], the categorization relevant to event-based energy metering contains *endurants* and *perdurants*:

- An *endurant* (or *stock*) has a conceptual meaning as an *instantaneous quantity*, applicable for example to the notions of voltage, current, power, or the time instant.
- A *perdurant* (or *flow*) acquires a conceptual meaning only when a certain *time interval* has elapsed. Examples are the time interval itself, integral quantities such as the RMS values, and energy calculated over a given time interval.

The *relationship between* endurants and perdurants seems obvious, but it encodes semantic meanings. Perdurants *hold the information* associated with the time of use (durations), linked with the natural time scale through the endurants representing the time tags (instants) and their *ordering* in time. Reference frames, clocks, timers, and event generators give us the sequence of endurants but also *establish relationships* between perdurants. Given a pair or perdurants $\{\Delta t_k, E_k\}$ containing the calculated quantity E_k referring the time interval Δt_k, the reference endurant could be set at the beginning, in the middle, at the end of the time interval, or in any other position. Authors *conventionally* associated all perdurants with the *end* of the time interval expressed as

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perdurant because in energy metering, the quantity E_k is reported only *after the corresponding duration has elapsed*. The notation Δt indicates a time interval $[t_i, t_i+\Delta t]$ that encompasses a sequence of a certain number m of elementary time steps lasting τ each. The perdurants of time included in the chained list of chunks are: $[t_i, t_i+\tau]$, $[t_i+\tau, t_i+2\tau]$, …, and $[t_i+(m\text{-}1)\tau, t_i+m\tau]$.

C. Self-Information and Mutual information

After Shannon, the Information Theory distinguishes between the *self-information* encoded in a single random variable and the *mutual information* encoded in a pair of variables to allow extracting knowledge about one variable based on the information about the remaining one.

The first concept is explored in the timer-based energy measurement mode. Knowing that the duration of the time interval Δt is constant, the *positional sequence* of average power values $P(t_k)$ for successive values of k in the time interval terminating at time instant t_k is related to the energy $E([t_{k\text{-}1},t_k])$ through the expression $P(t_k)=E([t_{k\text{-}1},t_k])/\Delta t$.

The second concept is illustrated by the progressive *energy* index $E(t_{k\text{-}1})$ and by the *variation of accumulated energy* $\Delta E([t_{k\text{-}1},t_k])$ allowing the computation of the next positional endurant term $E(t_k)=E(t_{k\text{-}1})+E([t_{k\text{-}1},t_k])$ forming the chained list of perdurants $\{E([t_0,t_1],…, E([t_{k\text{-}2},t_{k\text{-}1}], E([t_{k\text{-}1},t_k]), …\}$. The sequence of terms $\{E(t_1), …, E(t_k)\}$ represents the continuous update of the energy metered since the meter installation at time t_0. The term $E([t_{k\text{-}1},t_k])$ refers to the specific time interval $\Delta t_k=t_k\text{-}t_{k\text{-}1}$. As a matter of notation, considering mutual information, when the argument is an endurant, e.g., t_k for $E(t_k)$, the quantity represented is continuously updated with the natural time. Conversely, when the argument is a time interval, e.g., Δt_k for $E(\Delta t_k)$, the quantity represented by the $E([t_{k\text{-}1},t_k])$ refers to that time interval $[t_{k\text{-}1},t_k]$ only.

D. Rate of Events

Event-based observers generate irregular data traffic characterized by the *density of events* expressed as time-varying Rate of Events (*RoE*). The *RoE* is a new non-electrical information useful to link electric measurements from the time domain with the events from the transformed space denoted in [4] as *digital energy*. The number of *occurrences* produced by the event generator during a conventional *interval of natural time* expresses the process variability or volatility.

The outcomes of real life processes are not equally likely. Event-based agent makes a kind of belief that anticipates the energy behavior during the sub-sequent measurement experiment at the condition that the system will keep the same state as in the most recent past. An almost constant *RoE* may indicate operational conditions similar to those from the recent past, while an increased *RoE* could be an indicator of a real-life process' change. *RoE* is assessed by considering the count of the events falling within a given user-defined time interval $[t_{init},t_{final}]$ with duration multiple of τ. Inheriting from the classical timer-based metering making averaged values every 900 seconds, the same observational period can be fixed in order to count events falling in the sliding time-windows $[t_{j\text{-}900}, t_j]$. Each outcome is evaluated by considering the timing of events and represented through the *event counter* function $f(\Delta t_j)$ with integer and never negative outcomes.

An increased/decreased *density* of events means more/less changes. At long run, the sequence of *RoE* counts becomes a *Map of Events* (*MoE*). The *MoE* is a time-slotted data object living in the natural time –being linked to time by the relevant endurants – $MoE=\{([t_0,t_{900}],f([t_0,t_{900}])), ([t_{900},t_{1800}], f([t_{900},t_{1800}])), …, ([t_{85550},t_{86400}], f([t_{85550},t_{86400}]))\}$ that shows the variability of the density of events. The *RoE* terms could be *used industrially* to compare energy-related events occurring in different time periods and physical systems. Fig. 2 illustrates the count of *RoE* that slides along the arrow of *natural time* [19]. The real-case photovoltaic plant's example shown in Fig. 3 indicates the presence of high volatility in a given time period [5].

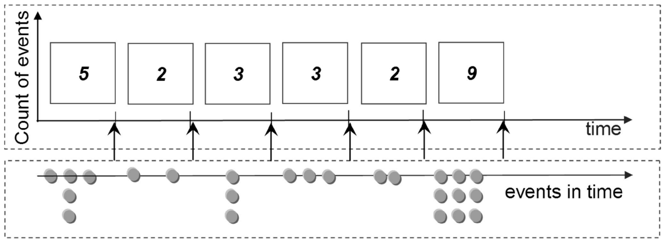

Fig. 2. The metering observer counts the Rate of Events.

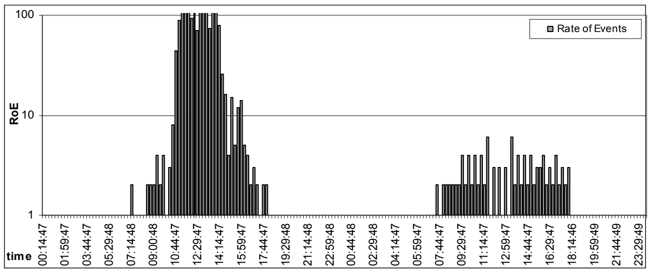

Fig. 3. The Rate of Events for a small-scale photovoltaic energy plant.

E. Stateless and stateful services

The EBM handles two different types of services:

- *Stateless* service, in which the relevant data is immediately used to provide the response to the service, then no memory of the result of that service is maintained. This happens when the average power referring to an elementary time interval is compared with the average power of the previous elementary time interval in order to check whether the difference between these values exceeds a given threshold. If the threshold is exceeded, an event is generated, otherwise the result is ignored.
- *Stateful* service, in which the response to the service is not provided at a given time, but depends on the occurrence of a condition involving a number of data, for which some memory has to be maintained. This happens when the energy values referring to a number of elementary time intervals have to be considered in order to check whether a given user-defined threshold is exceeded. This requires continuous monitoring of the system state. An event is generated each time the threshold is exceeded. Threshold setting issues are introduced in Section III and discussed in

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the examples shown in Section IV.

III. Event Generation for Energy Metering

A. Thresholds for detecting variations

The *energy* is conventionally associated with the *Riemann integral* of a function of power on an interval of time as it is defined by the formula (1). In practical applications [5], the perdurants of energy are computed by using numeric integration (Fig. 4), where the average power changes during the time interval, while the time step τ appears constant. The unknown a-priori shape of power should be always assumed as being irregular. When the event-based algorithm generates an event, the time tag t_j becomes defined.

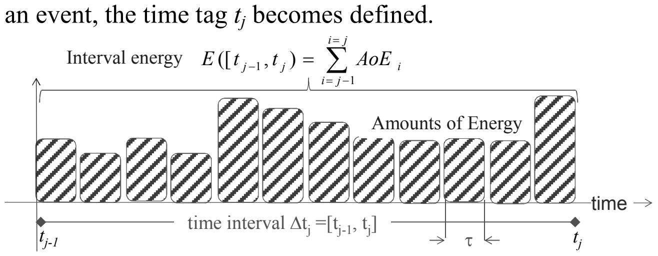

Fig. 4. Computation of the interval energy (total area).

The interval energy $E(\Delta t_j)=E([t_{j-1},t_j])$ is a perdurant given by the area between the graph of average power and the horizontal axis:

$$E([t_{j-1},t_j]) = \int_{t_{j-1}}^{t_j} P(t)\,dt \approx \sum_{m=1}^{\Delta t_j/\tau} P(t_{j-1}+m\tau)\cdot\tau \qquad (1)$$

Starting from the time instant t_{j-1}, until reaching the t_j generated by the *next* event, perdurants of time $[t_{j-1},t_k]$, with $t_k<t_j$, are characterized by "almost steady" and "smooth enough" average power, meaning that there is no major variation with respect to the previous trend. The average power $P(\Delta t_{j-1})$ that synthesizes said previous trend becomes the expected trend for the next succession of elementary time intervals. In other words, until the next event is generated, the expected trend is to maintain the average power *varying in the same known way* as in the previous period that is:

$$E\left([t_{j-1},t_k]\right) \approx P\left(\Delta t_{j-1}\right)\cdot\left(t_k - t_{j-1}\right) \qquad (2)$$

Upon occurrence of an event at t_j, the metering observer computes *once* the integral (1). This *compressive sensing scheme* drastically reduces the amount of data required to represent the signal [22]. The EBM identifies events by using an event generator capturing two types of conditions: quick stepwise jumps (a) and slow accumulated variations (b). The corresponding triggers are synthetically represented in Fig. 5. The first trigger acts in a memory-less way at the level of each elementary time interval, and is activated when the absolute value of the average power *variation* from one elementary time interval to the next one is higher than the threshold δ_1 (that is, when the absolute value of the energy in the corresponding elementary time interval exceeds the product $\tau\cdot\delta_1$). The second trigger acts on the basis of incremental variations of the accumulated energy with respect to the expected trend, when the absolute value of that quantity exceeds the threshold δ_2.

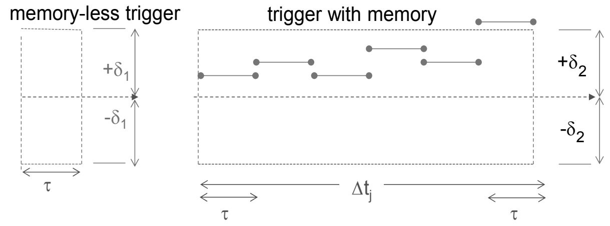

Fig. 5. The two triggers applied to the event-based energy metering.

In practical terms, the operation of these triggers can be seen as the application of specific filters able to recognize:

1. *Quick stepwise transitions*, thanks to a stateless filter depending on a threshold δ_1 applied to the variations of the average power referring to two successive elementary time intervals (3). The filter is stateless because any term $\Delta P([t_k-\tau,t_k])$ is independent of the previous ones, so that the event generator has no memory.

$$\Delta P([t_k-\tau,t_k]) = P(t_k) - P(t_k-\tau) \qquad (3)$$

A visual representation of the use of the threshold δ_1 is reported in Fig. 6, by showing the average power variations as Dirac-like pulses and identifying the event when the threshold is exceeded either with positive or negative variations. The elementary time step is $\tau = 1$ min. The Dirac pulses are located at the end of each elementary time interval. In Fig. 6, the time interval under consideration starts from the time instant t_{j-1}. The average power of the previous time interval $P(\Delta t_{j-1})$=3.5 kW is used as starting point to calculate the average power variation after the first elementary time step. In this example, the threshold is set to δ_1=4 kW. When the average power variation exceeds the threshold, the time instant corresponding to the end of the elementary time step at which the large variation occurred is identified as the time tag t_j marking the end of the time interval under consideration and, at the same time, the beginning of the next time interval. In the case reported in Fig. 6, the time interval ending at time tag t_j has a duration Δt_j=7 min, the energy corresponding to the time interval is $E(\Delta t_j)$=29.7 kWmin, and the average power is $P(\Delta t_j)$=29.7/7=4.24 kW.

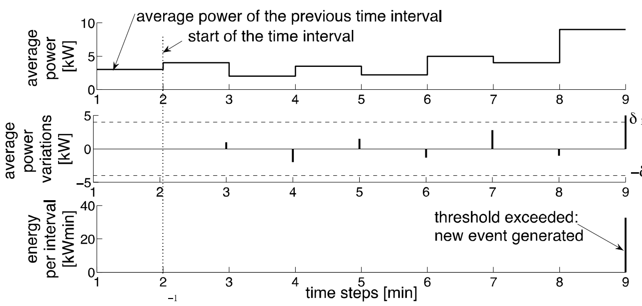

Fig. 6. Threshold δ_1 for average power variations.

The value $P(\Delta t_j)$ is then used as the reference to compare the average power variation occurring after the first elementary time step of the successive time interval.

2. *Slow accumulated variations,* by using a stateful filter based on a threshold δ_2 applied to accumulations of

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elementary unbalances of energy. Starting from the instant t_{j-1}, and considering a generic instant t_k successive to t_{j-1} by a finite number of elementary time intervals τ, the following accumulated energy *variation* is monitored:

$$\Delta E([t_{j-1}, t_{j-1}+k\tau]) = \tau \sum_{m=1}^{k} \left(P\left(t_{j-1}+m\tau\right) - P\left(t_{j-1}+(m-1)\,\tau\right) \right) \qquad (4)$$

Until the accumulated energy variation does not exceed the threshold δ_2 with memory, no event is generated, and otherwise an event is defined at the end of the elementary time step at which the accumulated energy variation occurred, identified by the time tag t_j.

A visual representation of the use of the threshold δ_2 is reported in Fig. 7, referring to a sequence of average power values at successive elementary time steps τ=1 min, starting from the time instant t_{j-1}. Let us assume that the average power representing the previous time interval is $P(\Delta t_{j-1})$=3 kW. This means that the expected average power is 3 kW at each elementary successive time interval. It is then possible to construct the evolution of the expected trend of the accumulated energy (represented in stair-wise form in Fig. 7). The threshold δ_2 is set in order to limit the variations of the accumulated energy (δ_2=10 kWmin in the example). In the example of Fig. 7, the time interval ends at time tag t_j and has duration Δt_j=10 min, the energy corresponding to the time interval is $E(\Delta t_j)$=45.7 kWmin, and the average power is $P(\Delta t_j)$=45.7/10=4.57 kW. The value $P(\Delta t_j)$ is an expected average power for the successive time interval. Fig. 8 shows the *de-trended evolution* of the accumulated energy variations, obtained by subtracting the expected trend from the accumulated energy entries shown in Fig. 7. This de-trended evolution is consistent with the right hand-side of Fig. 4 and is used for representation purposes to save vertical space in the figures [4]. In the example presented in Fig. 7 and Fig. 8, the sequence of average power values starts in a way consistent with the expected trend, then the accumulated energy starts growing to a larger extent, up to reaching the upper threshold and generating the new event.

B. Compatibility with classical energy metering

The EBM approach to energy metering can be adjusted to coexist with the classical TBM approach with regular time periods. It is sufficient to force the occurrence of an artificial event at predefined time periods, summing up all the energy per intervals found in the last regular time interval [22]. In order to preserve the effectiveness of the event-based representation, the timer-based energy (and *RoE*) computation may be run in parallel with the event-based thread by making the artificial event inactive for the purpose of representing a real-life process through the identification of relevant events.

C. Absence of communication and density of events

Until an event generator remains "silent", there are no messages directed to remote peers. When an event occurs, the related data travel over the communication channel. The absence of events/communication – provided that appropriate verification is carried out to exclude problems in the communication channels [1] – has a pivotal role because it indicates that the *system follows the previous (and expected) trend*. In the event-based metering approach, based on the fact that the pattern is not exceeding the thresholds on average power or accumulated energy variations, *any* remote observer can estimate the state of a system autonomously, without any further data being encoded in individual variables.

A large number of co-occurring unbalances of energy is trapped by the specific attribute *RoE*. Therefore, a substantially increased *RoE* during a certain time slot could warn about potentially compromised system operation.

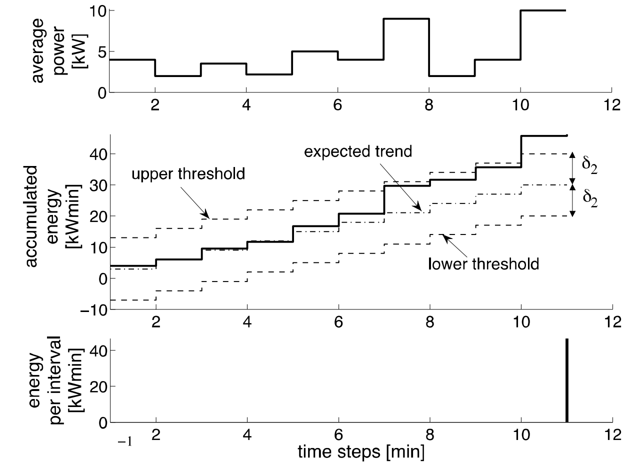

Fig. 7. Threshold δ_2 and accumulated energy trend.

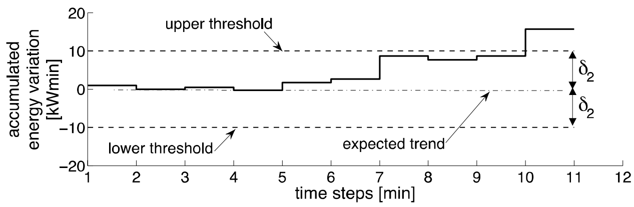

Fig. 8. Representation of the threshold δ_2 for accumulated energy variations.

D. Structure of the event-based data object

Following the previous illustration of the event generation modes, each time interval corresponds to a data object containing a number of attributes containing general information, endurants, and perdurants. In particular, for each energy meter labeled with a unique identifier MeterId:

- The general information is indicated by the MessageType attribute set up to indicate the distinction between timer-driven (TD) or event-driven (ED) modes.
- The endurant is the TimeTag attribute, introduced at the occurrence of each event.
- The perdurants are the time interval duration Δt_j, the energy counter $E(t_{j-1})$ at the previous time, the energy variation $E(\Delta t_j)$ during the last period, and the energy counter $E(t_j)$=$E(t_{j-1})$+ $E(\Delta t_j)$ at the current time.

On the basis of the above indicated values, the meter calculates the average power perdurant $P(\Delta t_j)$=$E(\Delta t_j)/\Delta t_j$ and associates it with the time interval Δt_j. Fig. 9 shows the contents involved in the data object. The *Rate of Change of*

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Energy (*RoCoE*) and the average power perdurant $P(\Delta t_j)$ are identical.

Furthermore, the *RoE* gives the ratio between the number of events occurring in the user-defined time period of analysis $[t_{init}, t_{final}]$ and the duration of the time period itself (e.g., the 15 minutes indicated in Section II.D). Thereby, each event detected in the time interval Δt_j increases by one the counter of the events in the calculation of the *RoE* for the time interval $[t_{init}, t_{final}]$ containing the time interval Δt_j.

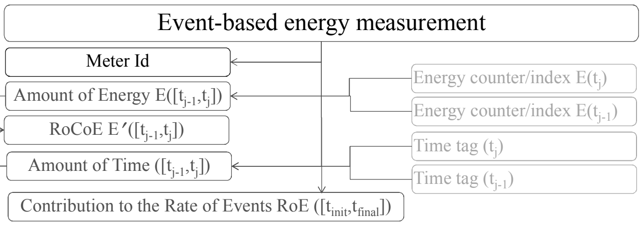

Fig. 9. Event-based energy metering data object.

E. Knowledge representation

The new event-based approach represents *energy* as a quantity associated with a *real-life process* occurring at an expected almost steady *RoCoE*. It requires the data object encompassing several attributes of different types. It is associated with the time interval (perdurant of time) and with the energy per time interval (perdurant of quantity). It reports the accumulated energy so far and the most recent *change*.

In synthesis, the knowledge representation in the event-based energy metering operates in stateless and stateful fashions at the same time, providing the following contents:

- The ordered sequence of average power per elementary time interval contains the stateless knowledge about the average power transients.
- The sequence of accumulated energy values contains the stateful knowledge on the historical evolution of the consumption.
- The sequence of energy per (unevenly-spaced) time interval and the corresponding *RoCoE* contain the stateful details of the process being metered.
- The *RoE* provides information on the details of the process under analysis in the time period under observation. It can also be used in a moving window-like observer, indicating the dynamics occurring in the metered system.

F. Reconstruction of the average power pattern

During the actual EBM measurements, the pattern corresponding to the average power gathered at successive elementary time intervals is not known. For the sake of comparison, in the cases shown in the examples of this paper, the average power values forming this pattern (denoted here as *base* pattern) have been measured and are available.

The time tags of the events detected and the *RoCoE* make it possible to build an *ED-reconstructed* pattern having the resolution in time equal to the one of the reference pattern. In the reconstructed pattern, the relevant aspects detected are represented in more detail, while the variations smaller than the given thresholds are averaged. In the same way, the *TD-reconstructed* patterns are obtained by using the timer-driven energy values, considering the average power constant between two successive time intervals (e.g., 15 minutes, 30 minutes, and 1 hour), and building the pattern having the resolution in time equal to the one of the reference pattern.

The quality of reconstruction of the base pattern P_{base} by using the *ED-reconstructed* patterns with data available from EDM measurements at given thresholds has been compared with the quality of the reconstruction of the base pattern carried out from the *TD-reconstructed* patterns with different regular time intervals. Let us denote with $M = T/\tau$ the number of elementary time intervals in the observation period T, with P_R the reconstructed pattern, calculated over the $m = 1,\ldots,M$ elementary time intervals, and with $P_\Delta(m,\tau)$ the absolute error

$$P_\Delta(m,\tau) = |P_{base}[(m-1)\tau, m\tau] - P_R[(m-1)\tau, m\tau]| \qquad (5)$$

The comparisons have been carried out by using some distance and error metrics. The distance metric d_E based on the step-by-step Euclidean distance between the base pattern P_{base} and the reconstructed pattern P_R is expressed as:

$$d_E = \sqrt{\frac{1}{M}\sum_{m=1}^{M}\left(P_\Delta(m,\tau)\right)^2} \qquad (6)$$

In addition, two error metrics [23] are used:

- Mean Absolute Error (*MAE*):

$$MAE = \frac{1}{M}\sum_{m=1}^{M} P_\Delta(m,\tau) \qquad (7)$$

- Weighted Absolute Percentage Error (*WAPE*, also known as MAD/Mean Ratio), and its characteristics have been discussed in [24], used instead of the classical Mean Absolute Percentage Error (*MAPE*) because the base pattern values could have very low or null values (in the latter case the *MAPE* could not be calculated):

$$WAPE = 100\frac{\sum_{m=1}^{M} P_\Delta(m,\tau)}{\sum_{m=1}^{M} P_{base}[(m-1)\tau, m\tau]} \qquad (8)$$

IV. Examples of Application

A. Dataset and reference pattern

The dataset used in this application is taken from a residential user. The elementary time step is τ=1 s. Fig. 10 shows the average power and the corresponding average power variations during an observation period of about one day (84,000 s). The dataset has many variations in the average power. Relatively large fast variations also occur inside the processes with higher consumption[1].

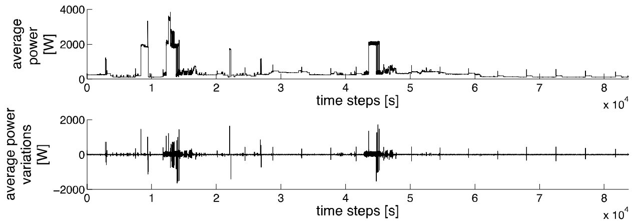

Fig. 10. Average power data and average power variations.

B. Application of the thresholds

The application of different thresholds δ_1 and δ_2 generates different numbers of events during the observation period. The

[1] Reductions of the variations in the dataset could be obtained by increasing the elementary time step, losing details in the process representation.

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conceptual difference among the two thresholds is that the application of the threshold δ_1 always refers to the *same* average power variations pattern, due to the stateless characteristics of the application of that threshold, while the threshold δ_2 is applied to a *stateful* energy variation pattern that changes depending on the history of the past variations.

A first example sets up the threshold δ_1 while maintaining the threshold δ_2 high enough to become inactive. The number of events generated decreases when the threshold increases, as reported in Fig. 11, changing in a monotonic way. Further examples are illustrated by varying the threshold δ_2 while maintaining the threshold δ_1 high enough to become inactive. In the case of Fig. 12, the total number of events does *not* change in a monotonic way. It is due to the stateful nature of the application of the threshold δ_2, according with which the accumulated energy variation patterns change because the threshold is reached in different time instants. In other words, while by lowering the threshold δ_1 there is an additive contribution of new events and the previous ones remain at the same time tags, when the threshold δ_2 is reduced the time tag of the previously detected events does not necessarily exist.

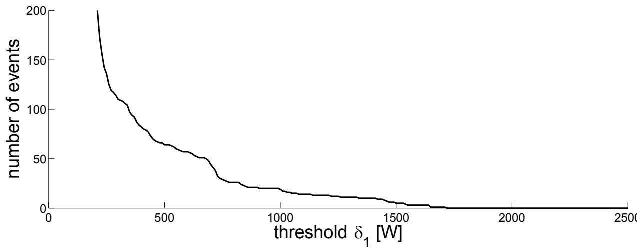

Fig. 11. Number of events depends on the average power variations threshold δ_1.

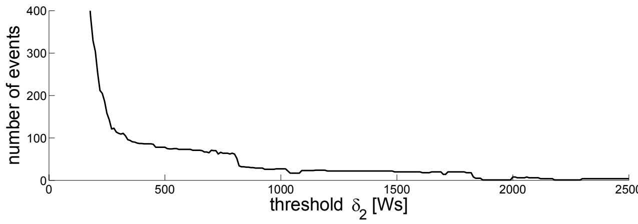

Fig. 12. Number of events depends on the accumulated energy variations threshold δ_2.

Fig. 13 shows how the accumulated energy variation patterns change for three cases with δ_2 = 250, 500 and 1000 Ws. For each threshold δ_2, the first representation indicates the accumulated energy variation and the threshold δ_2. The second representation contains the evolution of the accumulated energy in the successive time intervals (after each event generated, the accumulated energy is restored to zero). The third representation shows the Dirac pulses corresponding to the events, whose amplitude is equal to the energy per interval (i.e., the last value of the accumulated energy resulting in the time interval when the event is generated).

C. Considerations on data definition and threshold settings

In general, with the simultaneous application of the two thresholds the accumulated energy variation pattern changes due to the *combined effect* of these thresholds. The threshold setting has to be chosen in a suitable way to identify the *processes* [19]. This has to be done after a preliminary analysis of the average power patterns of the specific application, in such a way to identify the amounts of the variations and their distribution in time. The details of this analysis will be presented in a future contribution. In synthesis, there are three main aspects in the assessment of the processes gathered by event-based energy metering:

- The resolution in time of the dataset: conceptually the dataset could be available with an elementary time step as short as possible, leaving the possibility to the operator to pre-process the dataset to construct a new pattern with longer averaging time step in order to reduce the number of fast variations if needed.
- The setting of the average power threshold, aimed at recognizing the main processes containing large variations.
- The setting of the accumulated energy threshold, aimed at identifying deviations with respect to the expected trends.

More specific analyses can provide indications on possible dynamic setting of the thresholds, i.e., thresholds that can change during time depending on auxiliary calculations carried out in near real-time on the reconstructed patterns, or depending on external information linked to the timings of the patterns (e.g., with different thresholds in time periods during the day and during the night for industrial processes).

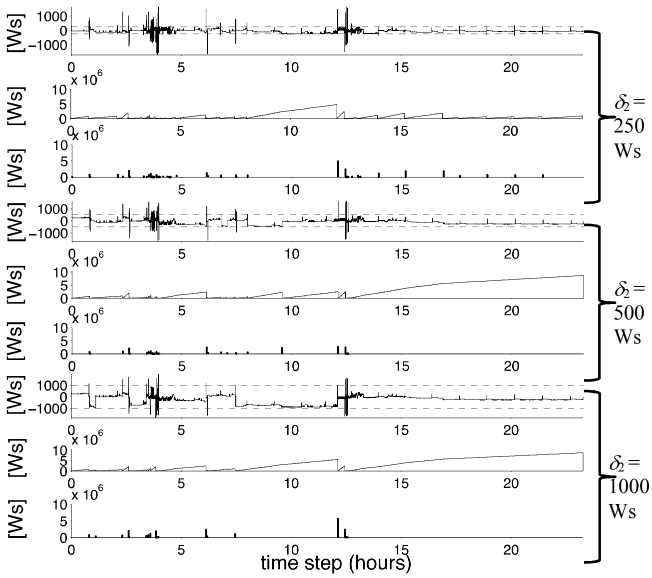

Fig. 13. Accumulated energy variation patterns depending on the threshold δ_2.

D. Reconstruction of the average power pattern from the event-based energy metering outcomes

In order to show an example of the ED-reconstructed pattern indicated in section III.F, Fig. 14 shows the reconstruction of the pattern of a time period, with thresholds set to δ_1 = 300 W and δ_2 = 300 Ws. The event-based approach maintains the crucial information on the large variations and changes from the expected trend, preserving at the same time the actual energy per time interval. Results of a quantitative assessment of the reconstruction, carried out through the calculation of the Euclidean distance (15) for a time period of

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23 hours[2], corresponding to the total number of elementary time intervals M = 82800, are reported in Table I. By considering timer-driven metering with data gathered at 15 minutes, 30 minutes or 60 minutes, the number of data taken in the day is 96, 48 and 24, respectively. For the TD-reconstructed patterns, the Euclidean distances are 245.5, 326.3 and 366.3, respectively. More generally, Fig. 15 shows the Euclidean distances found with respect to the TD-reconstructed patterns at time periods having 60 minutes as its multiple. The Euclidean distance falls to zero at a time resolution equal to the elementary time interval (1 s). For the sake of comparison, combinations of the thresholds δ_1 and δ_2 leading to the same numbers of points[3] have been found for the event-driven mode, calculating the Euclidean distance for the corresponding ED-reconstructed patterns.

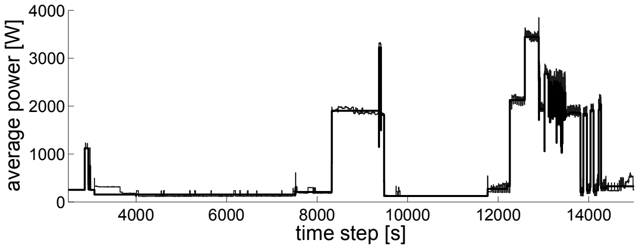

Fig. 14. Reconstruction of the average power through the *RoCoE* (zoom for a time period). The thin line represents the initial pattern at 1-second time step. The thick line represents the pattern reconstructed from the event-based energy metering outcomes.

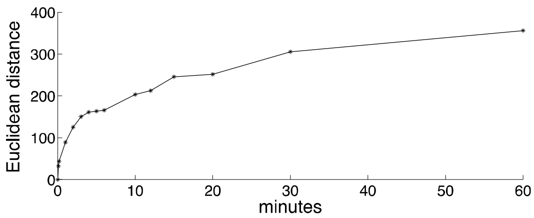

Fig. 15. Euclidean distances resulting from the pattern reconstruction by using timer-driven data.

The results obtained provide a clear picture of the remarkable properties of the event-driven approach to provide better reconstructions of the base patterns with a reduced number of points. For example, in timer-driven mode at the points with time resolution of 2 minutes, with 690 points in the 23 hours, the Euclidean distance is 125.5 (Fig. 15). In the event-driven mode, a solution with similar Euclidean distance (equal to 122.1, from Table I) is obtained with only 48 points, that is, by taking only about 7% of the points. An event-driven solution with 690 points, indicated in Table I, would have a Euclidean distance of 36.7. In turn, to get a Euclidean distance lower than 36.7, in timer-driven mode the time resolution should be lower than 10 s. From Table I, with time resolution of 6 s (i.e., with 13800 points) the Euclidean distance would be 32.0. Again, the ratio 690/13800 indicates comparable reconstruction capability in event-driven mode by using about 5% of the points needed in timer-driven mode.

TABLE I
EUCLIDEAN DISTANCES FROM TIMER DRIVEN AND EVENT DRIVEN RECONSTRUCTED PATTERNS

timer-driven			event-driven			
resolution	#points	d_E	δ_1 [W]	δ_2 [Ws]	#points	d_E
6 s	13800	32.0	2	2	13899	0.7
10 s	8280	43.4	6	10	8260	1.6
2 min	690	125.5	132	198	690	36.7
15 min	96	245.7	1500	600	87	107.1
30 min	48	305.6	1400	1300	48	122.1
60 min	24	356.1	1200	2000	24	259.7

Table II shows the error metrics calculated for the same cases indicated in Table I. The *MAE* and *WAPE* calculated over the whole period are always lower for the reconstruction based on the event-driven results. It could seem that some differences between the indicators are not so high between the timer-driven and the event-driven results. However, it has to be considered that the errors are calculated by taking into account the absolute deviations on all the M points. For most of the points, the base pattern is rather low, and for these points the contributions to the absolute errors are relatively low. The true difference occurs for a limited number of points. This fact may be clearly seen by zooming at the absolute errors. The Fig. 16 example shows the absolute errors corresponding to the two cases with 690 points indicated in Table I, represented for a time period in Fig. 14. The absolute errors with the TBM data reach very high values (the maximum is 1647 W, even though the *MAE* is 31.9 W). Conversely, the absolute error in the EBM data remains limited (the maximum is 179 W, with a *MAE* of 25.9 W). This difference clearly indicates the substantial benefit of the EBM representation for what concerns the absolute error reduction.

TABLE II
MAE AND *WAPE* INDICATORS FROM TIMER DRIVEN AND EVENT DRIVEN RECONSTRUCTED PATTERNS

timer-driven			event-driven			
resolution	*MAE* [W]	*WAPE* (%)	δ_1 [W]	δ_2 [Ws]	*MAE* [W]	*WAPE* (%)
6 s	5.70	1.62	2	2	0.38	0.11
10 s	8.46	2.40	6	10	1.02	0.29
2 min	31.9	9.02	132	198	25.9	7.33
15 min	89.6	25.4	1500	600	83.4	23.6
30 min	118.9	33.7	1400	1300	93.7	26.5
60 min	157.2	44.5	1200	2000	145.8	41.3

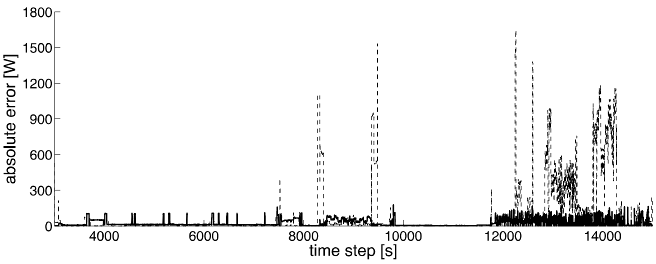

Fig. 16. Absolute error of the initial pattern reconstruction for a time period, from timer-driven data (dashed line) and event-based data (continuous line).

From the EBM results, the *WAPE* growth mainly depends on the usage of high values of δ_1, with which it becomes

[2] The reference pattern has data for 84,000 s, which is not a period multiple of one hour. The time period considered here has 82,800 s and is multiple of one hour, to make it possible to obtain an exact time partitioning by using timer-driven data taken each 60 minutes.

[3] For the 15-minute case, the conservative solution with 87 points has been considered, as a solution with exactly 96 points has not been found.

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inefficient to follow the load pattern variations. Besides the advantages on load pattern reconstruction, the main aspect of the EBM approach remains the *exact/true* representation of the integral quantity (energy) associated with the consumption pattern between successive events.

E. Using counts of events

Additional information may be found by observing the dynamics of the metered process, indicated by the *MoE* assessed within a given time period in a *moving window* mode. An example is reported in Fig. 17, referring to the same thresholds used in the previous Section IV.D, using a time step of one minute to group the events and considering a moving window length of 15 minutes before the time instant of observation. The *RoE* traces the intensification of events. Upon *RoE* increase - if the *RoE* increase can be interpreted as unwanted system activity-, the operator can perform different actions, from sending alerts, starting specific procedures to recognize the process under activation in order to anticipate some components of the possible evolution of the system in the successive time instants, or just monitoring that the process is evolving as scheduled.

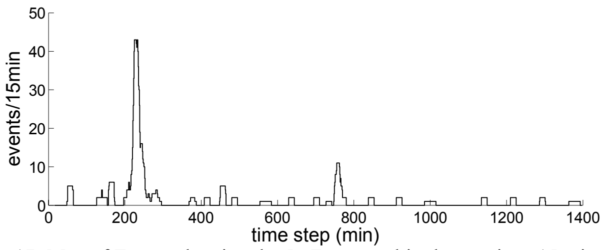

Fig. 17. Map of Events showing the *RoE* occurred in the previous 15 minutes with respect to the instant of observation, with events grouped by minutes.

V. Concluding Remarks

In the described approach, the notion of *event*, associated with the integral quantity representing the energy measured from one event to another, has been used to formulate an effective energy metering scheme. This scheme provides integral quantities at discrete steps. When an event occurs, the integral quantities (i.e., the perdurants of duration of the time interval, energy and average power between events) are determined. These quantities represent the energy conservation in the process and have no intrinsic error, as required in an energy meter. The information on the total energy counter is transmitted, together with the other perdurants, over the communication channels, avoiding the need to recalculate them by the receiver.

The "instantaneous" values of power used to determine the average power for each elementary time interval and the average power at each elementary time interval itself, are seen inside the meter but are not communicated outside the meter, to avoid sending an excessive amount of information containing only small variations over the communication channels. The remarkable advantage of the EBM approach is that it filters out these small variations to maintain only the values corresponding to the time intervals more representative of the evolution in time of the load pattern. On the basis of these values, the power pattern is reconstructed by using a number of data very limited (i.e., a few percent in the examples shown in this paper) with respect to the number of data that would be needed by using timer-driven data gathered at regular time periods providing a similar quality in the pattern reconstruction. After an event has been detected, the expected trend of the future evolution in time of the power is established depending on the previous average power. As far as no new events are detected in real-time, the actual evolution of the average power pattern estimates the trend within the limits established by the thresholds imposed. This provides a baseline for the future evolution of the pattern.

The EBM approach has a number of convenient applications, starting from the most natural one – providing data for billing. Metering for billing purposes is a continuous process. Billing generally requires a single energy value in a predefined period (e.g., one month). In order to maintain consistency with the billing practices, the EBM scheme is easily aligned with the time horizon used for billing, by adding a dedicated "event" (occurring once a month) to provide the precise energy value to be used for billing. Multi-period billing rates may be accommodated in the same way. While satisfying the billing task, in real-time operation the EBM reports energy at non-regular time intervals, enhancing the knowledge on the consumers' average power patterns as indicated below. If the number of events increases in a given time period, the *RoE* indicates the higher activity occurring in the process. User interprets the meaning of a *RoE* increase by establishing whether it is a normal feature of the process, or something unexpected is happening. In the latter case, key information, also containing the energy content of the evolving process, is available for diagnosis purposes.

In the industrial perspective, the event-based energy metering adds value by a mix of aspects such as meaningful data compression capability, preservation of the energy referring to successive time intervals, detailed representation of real-life processes, flexibility of operation with variable thresholds for enhancing the knowledge on the characteristics of electrical energy usage, and analytical accounting of the energy being transformed by a specific real-time process.

In the computational perspective, the event-based energy metering approach allows re-distribution of the computational effort between software agents. Industrial multi-core energy meters enable high-power parallel processing of information. Before the detection of the next event, the local CPUs remain available to compute control variables, conditions, and decentralized control actions. Examples of new business usages are periodic cross-check of the total energy, provision of additional information for customer profiling, and discovery of specific characteristics of real-life processes.

In the new generation of smart meters, local processing of information will make energy management at the user's site more efficient. Event-based energy metering is ready to be adopted to identify the details of the energy usage by processing the data available in the meter with different pairs of thresholds, to highlight different portions of the information that may describe the monitored process in a better way.

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Mikhail Simonov (M'13). Ph.D. at Energy Dept. of Politecnico di Milano (Smart Grid related) and M.Sc. from Moscow State University (Computer Science, AI related). Multi-disciplinary and cross-sectorial experience in several European Industries, Service companies, and Finance sector. He worked in management consultancy, in private industrial companies and software houses. Project leader and manager for more than 15 years. He performs R&D activities since 1999.

Gianfranco Chicco (M'98, SM'08) received the Ph.D. degree in Electrotechnics Engineering from Politecnico di Torino (PdT), Torino, Italy, in 1992. He is a Professor of Electrical Energy Systems at PdT. His research interests include power system and distribution system analysis, energy efficiency, distributed multi-generation, load management, artificial intelligence applications, and power quality. He is a member of the Italian Federation of Electrical, Electronic and Telecommunications Engineers (AEIT).

Gianluca Zanetto received the M.S. degree in electronic engineering from Politecnico of Milan in 1985, specializing in process automation. He designed microprocessor-based devices for electric power measuring and control, had experience in avionic electronics developments. Gianluca was one of co-founders of TEAMWARE in 1988, where he holds now the position of Chief of Energy Products and Research Areas.

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