Consumption temporary density for the detection of water leakages in real-time

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***Abstract*—Detecting water leakage is a major challenge. Usually, specific meters are used to monitor water consumption. However, conventional meters are not capable of detecting an abnormal consumption such as an eventual leak. Due to recent advances in technologies and the emergence of the Internet of Things paradigm, a new kind of smart water meter has appeared. These meters provide further options for monitoring water consumption. In this paper, a new water leakage indicator, called Water Leakage Indicator based on the Consumption Temporary Density (WLICTD), is presented. The leakage detection process is based on a computation of temporal density for water consumption. WLICTD can distinguish an abnormal consumption, i.e., a leak situation, from a normal daily consumption. The proposed indicator has been evaluated using a set of real water consumption data obtained from a smart meter installed in a university restaurant in France. Results reveal the strength and efficiency of the proposed indicator in detecting all water leaks situations within a convenient period of time.**

***Index Terms*—Water leakage detection, intelligent meter, IoT, temporary density.**

I. Introduction

A water leak is an event that tends to happen in unexpected times. The most important thing is to be able to fix it quickly enough in order to both limit the damage and to minimize the costs as well. In the majority of cases, leaks can not be detected early enough when the damage is minor or under normal consumptions. The emergence of the Internet of Things (IoT) paradigm has open new perspectives in several fields [1], [2]. Since these recent years, enhanced sensors have been developed. They are able to measure with a high precision the consumption and to transmit the data several time a day. They may be used in order to detect the leaks. Water Distribution Networks (WDN) are characterized by numerous nodes and a high number of branches. Identifying the vanishing pipes is therefore a very difficult task. Moreover, a constant, small and diffuse flow cannot be detected by conventional measuring instruments especially since the consumption data are generally only recorded and transmitted over a long period of time. This can lead to great losses of water [3]. In Europe, 11% of the European population and 17% of its territory has been affected by water scarcity according to the European Commission's estimate [4]. The importance of detecting leaks consists in preserving water resources, avoiding consequential damages in the WDN and saving water demand. In addition, a water leakage can affect the water quality by introducing infections into the WDN and have important consequences on the health and safety of the population [5].

We aim in this paper to provide a new water leakage indicator based on the consumption temporary density.

This article is organized as follows: In Section II, we review the state of the art on water leak detection. Section III describes the platform that is used to collect the data on the web, describes the raw water consumption data and introduces the daily load curves generally used to monitor water consumptions. In Section IV, we propose a Water Leakage Indicator based on the Consumption Temporary Density (WLICTD) which is based on a temporary density for detecting water leakages. In Section V, the proposed approach is validated with experimental examples of water leaks in a university restaurant and compared to the existing approaches.

II. Related works

The IoT [6] is an enlargement of the Internet's architecture and consists in a full integration of connected devices. These devices can be Cyber-Physical Systems (CPS) that communicate with each other but also with the servers and the users [7]. The IoT concept aims to enhance WDN in a more widespread way [8]. IoT water meters can immediately record and transmit events that correspond to the small amount of water consumed in a few period of time like minutes or seconds. Thus, measured consumption are collected and stored on a data center from where they are available to be analyzed. Therefore, it is possible to use the data measured during these small time stamps or intervals to detect the leaks.

A load profile is the key concept to analyze consumption and to separate the normal consumption from water leaks and other abnormal water needs. A load profile is the variation of water load with time. In a WDN, a load profile represents the amount of water that flows through a measurement point. Therefore, the area under the load curve gives the total units of water generated or consumed. In addition, the cumulative load curve represents the evolution of the index over a specific time. The load profile is thus the derivative of the cumulative load curve over the same period. As the water consumption never remains constant rather it varies time to time and these variations in load can be plotted on half hourly or hourly basis or even every minutes for the whole day. The curve thus obtained is known as daily cumulative load curve but it can also be extended for any period of time, i.e., it can be drawn for a month or for a year too. It can be seen that the load profile or the cumulative load curve are simple and efficient tools to evaluate the water use and demand, but also the efficiency and reliability of water transportation.

In the context of measuring water, a lot of different principles and algorithms have been proposed in various research works for purposes like estimating the quantity of waisted water, leaks detection and control, monitor the user consumption, reduce the time required to repair the leak, etc. The authors of [5] defined a Minimum Night Flow (MNF) that consists in a threshold defined for an isolated area where the demand of water is generally low. Despite the fact that the MNF performs adequately regarding leak detection, the principle of minimum night-time flow rate remains unreliable when water demand is high. In [9], a method based on a Fuzzy Logic Decision Maker (FLDM) has been proposed to detect the leaks. It is based on a technique that relies on fuzzy sets to provide a kind of rough model of the WDN that takes into account its typology (material, length, diameter and age of pipes), environment (demand, topography and operating pressures) and even its operating conditions (population size, housing and socio-economic characteristics, living standards). This technique is complex and requires a lot of information about the materials. Techniques based on the sensor fusion of data have been used in [4] and [10]. However, they are not efficient to detect all the leaks. The approach proposed in [11] detects the leaks by being based on the learning of artificial neural networks, but this approach needs a large data set. The work in [12] associates a MNF threshold with another threshold that is a Period Without Null Consumption (PWNC). It is able to detect most of the small water leaks during the day by using the water flow circulating in a measurement point. In addition, the detection of large leaks is based on the maximum load curve. This complete approach is based on data sampled every minutes and requires a lot of time with big amounts of data.

In this article, we propose a leak detection algorithm that is based on the temporarily density of water consumption. This new approach takes into account the water consumption in a temporal manner by using real-time water consumption data. The data are collected and analyzed iteratively every minutes and allows to detect the leaks in a period of only some hours.

III. Data collection

The objective of this paper is the development of an indicator able to detect water leakages in a WDN. For this aim, we use a data set that consists in daily water consumption recorded in a university restaurant. This section first provides a detailed description of the platform used to generate the data. Then, the acquired data are explained.

A. Data capture platform

The model of the WDN and the principle of the recording platform installed in a university restaurant is depicted by Figure 1. The water consumption is monitored by a single smart meter. This water meter is a connected object with enhanced communication capabilities, i.e., that allows the measurement and transmission of the information about water consumption. More specifically, this meter allows the detection of a pulse which represents one full rotation of the small turbine which is inside the water meter. When users consume water through different devices (tab, dishwasher, heater, toilet, ...), the water passes through the turbine. Each time a liter of water is consumed, the turbine completes a rotation and thus generates an event (or a pulse). The produced data consists in time intervals taken to consume a liter of water that are send on a remote web server. This allows a real-time daily monitoring and control of the water consumption in the WDN.

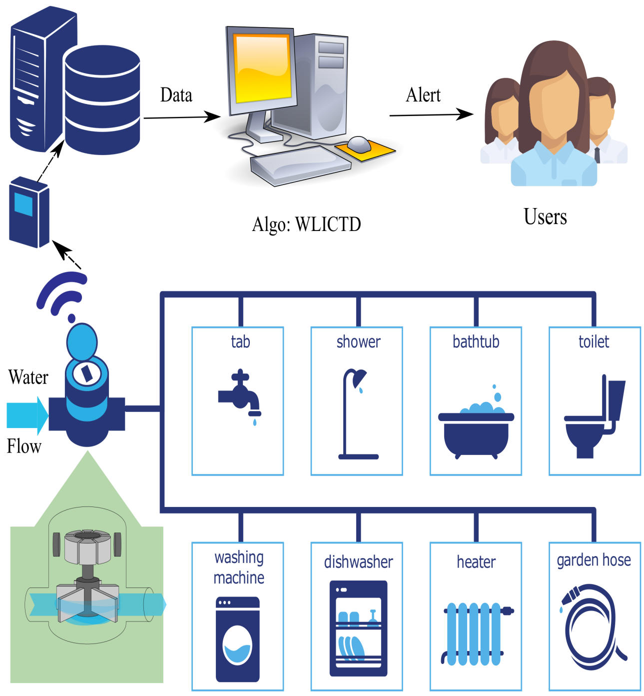

Fig. 1. The IoT platform in an integrated building [12]

B. Data description

As explained in the previous section, we use the data generated by a smart meter to detect water leakage. These data correspond to time lapses in milliseconds: $\triangle t_i = t_{i+1} - t_i$, such as for each $\triangle t_i, \forall i \in I$, a liter of water is consumed. One can note that I is the number of data and t_i is the current time. The evolution of the water consumption at the university restaurant is depicted by Figure 2 for the period from January 17th, 2018 to July 17th, 2018. The red points on Fig. 2. (a) correspond to the pulses which indicate the consumption of one liter of water at each time lapse. The blank between red points stands for weekend and holiday periods. The curve on Fig. 2. (b) depicts the accumulated consumption over time.

From this data set, it is possible to produce the load curves. Daily load curves can be viewed as progressive curves that represent the real cumulated water consumption at precise instants of a day. These curves facilitate the water consumption analysis. A load curve always begins with a zero value,

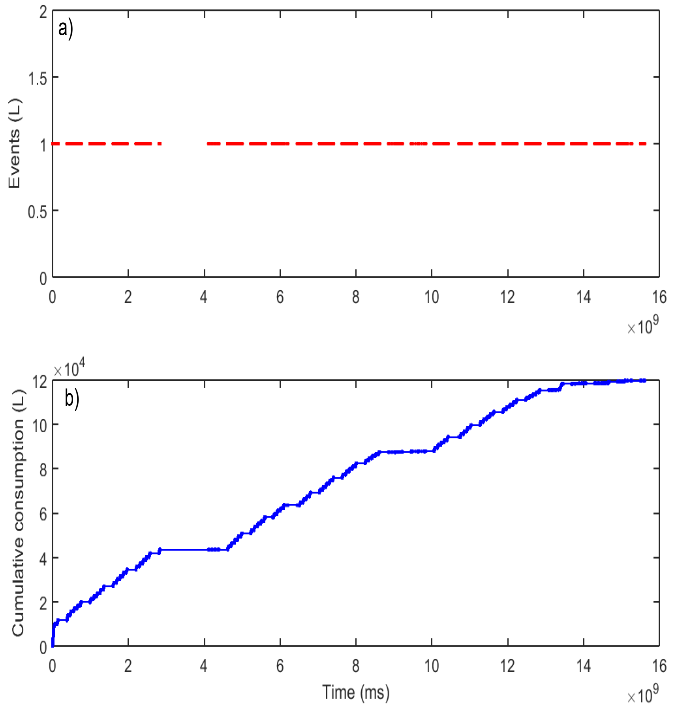

Fig. 2. Raw data of restaurant's water conception from January 17th, 2018 to July 17th, 2018

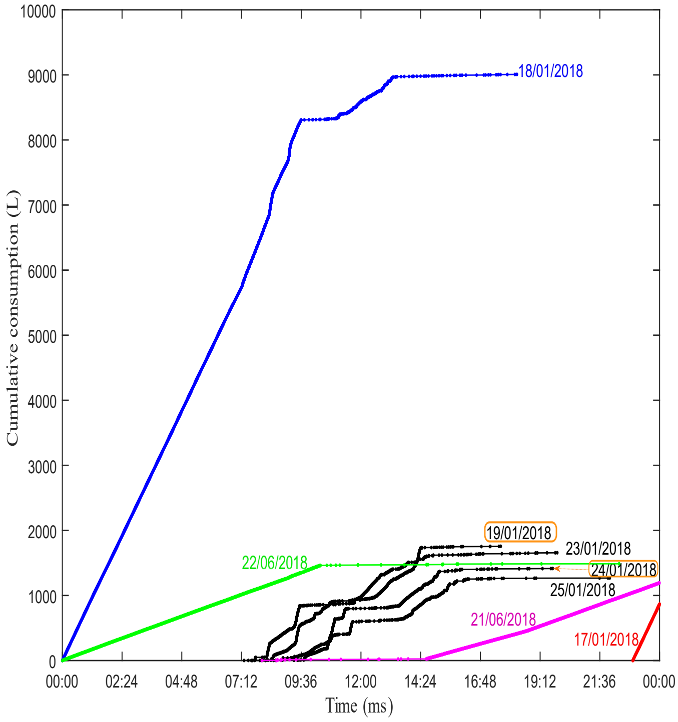

Fig. 3. Example of daily load curves of water consumption.

$C(t_0) = C(0) = 0$. At any given instant t_i, the curve is given by $C(t_i) = C(t_{i-1}) + 1$, since for every time gap $\triangle t_i = t_i - t_{i-1}$ a liter of water is consumed. The last value of the load curve corresponds to total water consumption of the day. Figure 3 illustrates several daily load curves. A preliminary observation shows that the behavior of the load curves changes from one day to another. Each curve presents a different distribution, this means that water consumption is not regular but varies over time. A deeper observation reveals some similarities between certain curves (i.e, black load curves), which can be explained by the usual activities of the university restaurant. The initial growth of the black curves corresponds to meal preparation during which water is consumed. Thereafter follows a stabilization period which is interpreted by the eating time (when water is less consumed). As soon as eating time is over, a cleaning step is performed in the restaurant, which explains the increase of the curve after its stabilization. Despite the commonalities presented by these curves, it remains very difficult to find an accurate model capable of representing all of them. The remaining colored curves are special curves that illustrate abnormal days (leakage situations). The red curve represents the beginning of a leak at the end of January 17th, 2018. This leak was not detected and it continued until the following day, i.e., January 18th, 2018 (represented by the blue curve), it was detected that mid-day. The second leak started on June 21th, 2018 and was detected on June 22th, 2018. It is depicted by the curves respectively in pink and green. In this paper, we aim to detect these leaks as early as possible for allowing a faster intervention and reducing potential damages.

IV. Water Leakage Indicator Based on Consumption Temporary Density

In order to detect water leakages, we propose to compute the temporal density of the water consumption. This density was used in [13] and [14] to analyze and measure the progress of random events over time. For each instance t_i, the temporal density $D(t_i)$ is computed and defined by:

$$D(t_i) = \lambda^{t_i - t_{i-1}} D(t_{i-1}) + 1 \quad (1)$$

In (1), t_i stands for the current time and t_{i-1} represents the latest time of the density update D. $\lambda \in]0, 1[$ is a parameter named the fading factor which reflects the rate in which the density decreases with time. The value of λ is adjusted through empirical tests with respect to the constraint of minimizing the water leak detection time. Thus, D_{t_i} is the density at time t_i. Using this function, it is possible to measure the quantity (number) of water that has been consumed over a period of time. The density D is computed in an incremental way. Upon the consumption of one liter of water at the instant t_{i+1}, the density is updated by adding one liter of water to the old density attenuated in time. It is important to mention that at the instant t_0 that corresponds to the instant of the initialization of the density, the density D_0 is null, since there is no consumption at the beginning of the day $D(t_0) = D(0) = 0$. As this function depends on the time elapsed between the time of the last density update and the current time, it gives a global view of the water consumption profile. Thus, if the

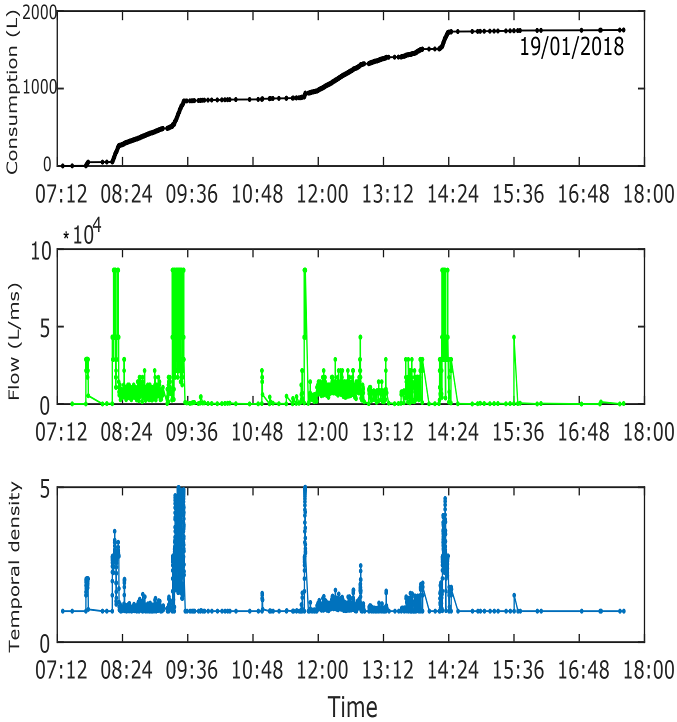

Fig. 4. The temporal density of water consumption during a typical day with $\lambda = 0.5$ and its load curve.

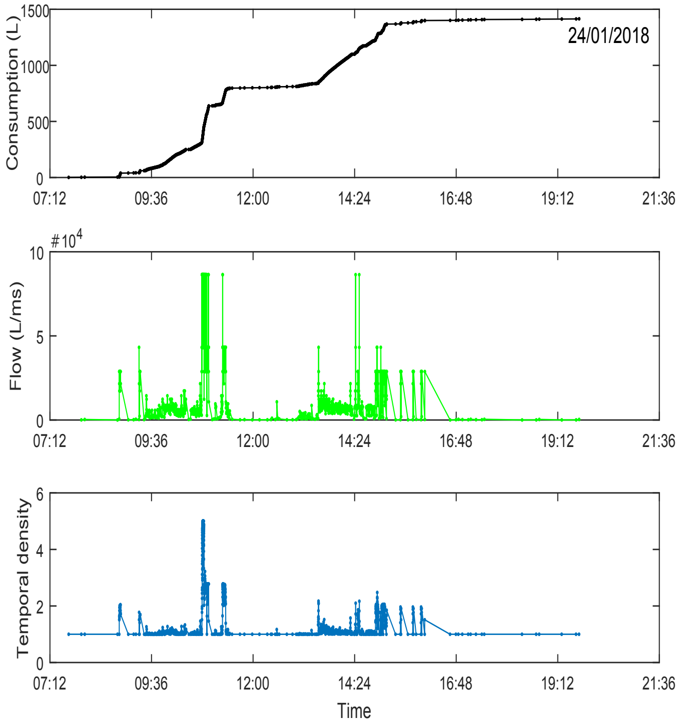

Fig. 5. The temporal density of water consumption during a typical day with $\lambda = 0.5$ and its load curve on 24/01/2018.

water consumption is regular, the density is low, whereas if the consumption is abnormal, the density is high.

Algorithm 1:

WLICTD (Water Leakage Indicator Consumption Temporary Density)

Determine the threshold.
for i = 1 : n **do**
  Compute the temporal density $D(t_i)$ at the instant t_i
  if $D(t_i) \neq 1$ **then**
    if $\triangle t_i > threshold$ **then**
      Leak detection
      Break
    end if
  end if
end for

end

Figures 4 and 5 depict examples of the temporal density evolution for water consumption during a normal day (i.e. a day without water leakage). We can observe that a high consumption implies a density greater than 1 since a big consumption implies a successive and rapid consumption which means that time gaps between the consumption of each liter are small, and as $\lambda \in]0, 1[$ this implies that $\lambda^{t_i - t_{i-1}} > 0$ which means $D(t_i) > 1;\ i > 1$. Whereas if the time gaps are large (which means there is a slow consumption) then $\lambda^{t_i - t_{i-1}} = \exp((t_i - t_{i-1}) \ln \lambda)$ approaches towards zero thus the density equals 1. According to the density computation for every day with $\lambda = 0.5$, a threshold has been defined by the maximum of the time deviations during periods of consequent consumption:

$$threshold = \max_i(\triangle^*(t_i)) = \max_i(t_{k_i} - t_{L_i}), \qquad (2)$$

where $D(t_{k_i}) = D(t_{L_i}) = 1$ and $\forall j \in]k_i,\ L_i[,\ D(t_j) \neq 1$. Since the data consists of time gaps $\triangle t_i$ so in order to detect the leaks, the temporal density is instantaneously calculated using $D(t_i) = \lambda^{\triangle t_i} D(t_{i-1}) + 1$; $D(t_0) = 0$. Then this value is compared with the value 1 and if $D(t_i)$ is different from 1 then we compare the difference in time with the threshold. If $\triangle t_i$ is higher than the threshold then we have a water leak. Otherwise, we redo the work but this time, the time difference is taken: $\triangle t_i;\ i = s1, \cdots, s2$ such as $\forall j,\ s1 \leq j \leq s2;\ D(t_j) > 1$, then we compare it with the threshold. This is illustrated by algorithm 1.

V. Applications and Comparison

A. Applications

Now we aim to apply the previous algorithme to our data set from the university restaurant. Thanks to the WLICTD algorithm, we succeeded to detect all water leaks within a period of approximately 3 hours. Figure 6 illustrates the temporal density versus time in seconds for two abnormal days (January 17th, 2018 and January 18th, 2018). Our approach allows to detect this leak within a period of 3 hours 11 minutes 13 seconds. Figure 7 depicts the temporal density versus time in seconds in two abnormal days on June 21th, 2018 and June 22th, 2018 respectively. Using our approach, this leak was detected within 3 hours 11 minutes 09 seconds.

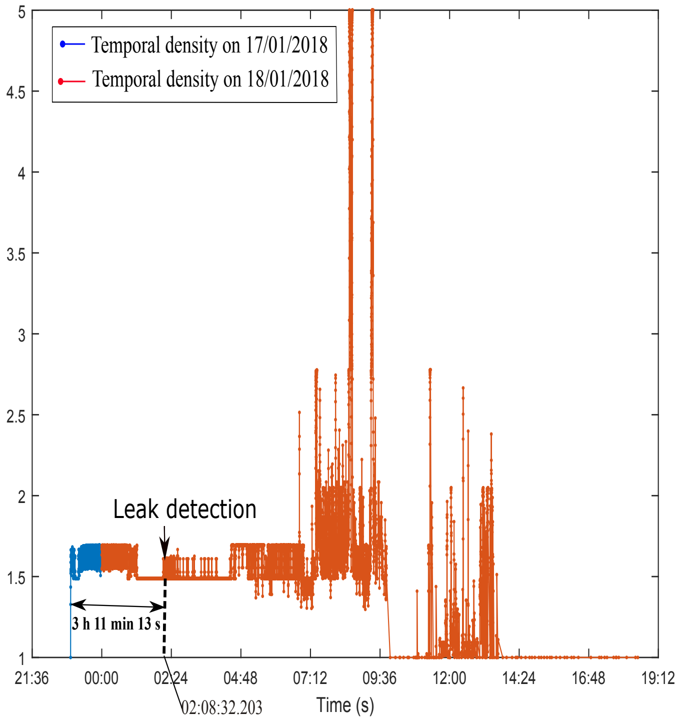

Fig. 6. The temporal density of water consumption during a day.

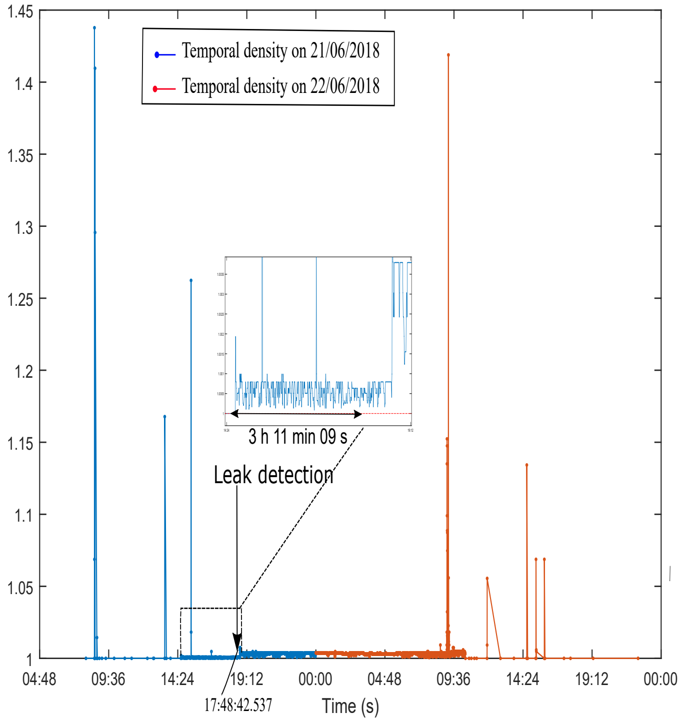

Fig. 7. The temporal density of water consumption during a day.

The choice of the parameter involved in computation, the temporal density λ is very important. For example for our data, the value $\lambda = 0.1$ does not allow to detect the water leak since the temporal density is equal to 1 for all the differences of time. In addition, the value $\lambda = 0.99$ makes it possible to detect the water leak after 14 h 33 min 09 s. So, the detection time is very long. It turns out that the values of λ between 0.4 and 0.9 provide good results. One needs to do more experiments to find a "universal" value of λ .

B. *Comparison between methods*

Detecting water leaks by classical methods takes a long time. The use of the maximum curve [6] to detect water leaks is reliable in periods when there is no consumption like nights in the university restaurant. Similarly, we can use the MNF to detect leaks at night [5], [6]. With data sampled per hour, we calculate the MNF which is equal to the maximum number of liters of water consumed overnight during normal days. The night at the university restaurant must start at 7:00 p.m. when the university is closed and end at 6:00 a.m. (at the opening of the university) which are represented by green arrows in Figure 8. Moreover the MNF is fixed by 37 (L/h).
The maximum curve approach detects the leak of June 21, 2018 after 9 hours 22 minutes and the leak of January 17th, 2018 the next day, in a period of one hour and 34 minutes, this is due to the starting of the leak which happened in the night corresponding to a period without any consumption in a normal situation. It turns out that the MNF is very efficient at night. Since it detects the leak of January 17th, 2018 after 5 minutes. The second leak which started at 14:38 during the day is detected only when the night period started which correspond to 4 hours and 22 minutes after (see Figure 8). In any case, the WLICTD algorithm allows the detection of both leaks within 3 h 11 min. We claim that the new approach based on the consumption temporary density is very efficient during the day and in general during a period of substantial consumption compared to the existing methods. The MNF approach is still the best one for the night periods. Therefore in order to improve detection of water leaks, we suggest a mix of the WLICTD and MNF methods. WLICTD is applied during the day or during periods with substantial consumption and MNF is used at night or during periods with no consumption as weekends or holidays. So to detect water leaks on weekends, we defined a threshold representing the maximum consumption on normal weekends which is equal to 3 liters of water in the university restaurant. Figure 9 illustrates the weekend water leak detection based on a threshold shown in red and the blue curve represents the load curve on March 24th, 2018.

VI. Conclusion

In this article, we have proposed a new approach for detecting water leakages. The detection process relies on the computation of a temporal density for water consumption. This density provides a reliable description of users' behavior in time, i.e., a water consumption profile over time which allows the recognition of abnormal activities such as high water consumption or water leakage. Our approach is named *WLICTD* for Water Leakage Indicator based on Consumption Temporary Density and it is able to detect water leaks in

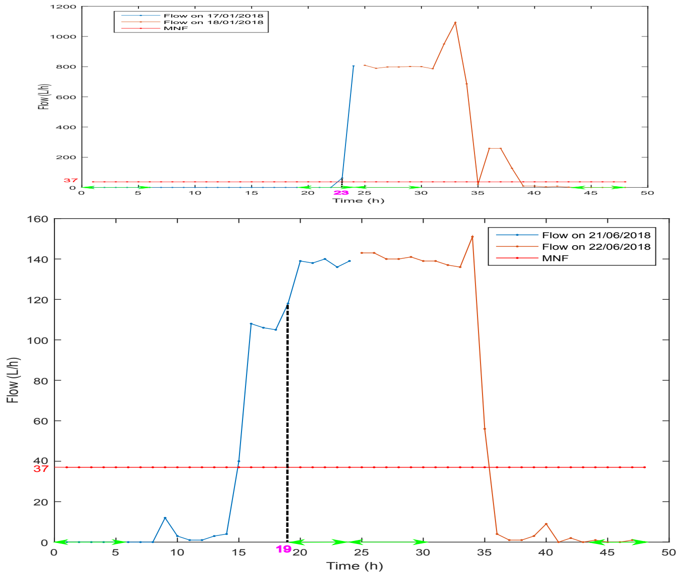

Fig. 8. Detecting a water leak by MNF.

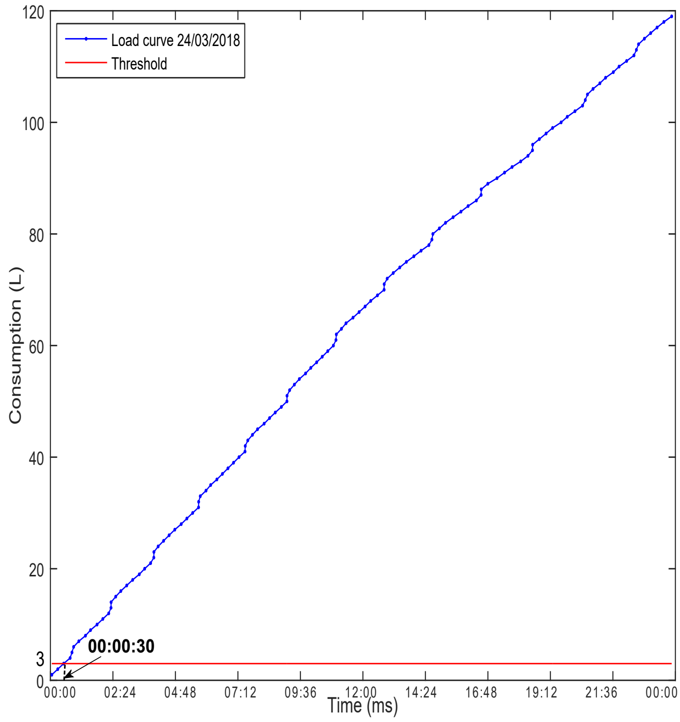

Fig. 9. Detecting a water leak in a weekend day.

approximately 3 hours. This approach allows to reduce the fixing time and thus to minimize the potential damages caused by the leak compared to other detection methods. On the other hand, the use of raw data simplifies the application of the approach. It turns out that the *WLICTD* algorithm is very efficient during periods of substantial consumptions compared to other approaches. It is used to detect water leaks at a university restaurant during the day and the MNF approach seems to be still the best for night periods. Looking ahead, we intend to investigate the performance of our indicator in complex environments such as smart homes where users behavior is highly variable and fluctuating. Moreover, we aim to exploit artificial intelligence techniques in order to improve the WLICTD algorithm through a better selection of the λ parameter used in the temporal density function.

VII. Acknowledgment

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