2014 International Joint Conference on Neural Networks (IJCNN)
July 6-11, 2014, Beijing, China

Computational Intelligence in Smart Water and Gas Grids: an Up-to-Date Overview

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***Abstract*—Computational Intelligence plays a relevant role in several Smart Grid applications, and there is a florid literature in this regard. However, most of the efforts have been oriented to the electrical energy field, for which many contributions have appeared so far, also facilitated by the availability of suitable databases to use for system training and testing. Different is the case for the water and gas scenarios: this work is thus oriented to present the state-of-the-art techniques for these grids, from 2009 to date. In particular, the focus is on load forecasting and leakage detection applications, that are the most addressed in the literature and present the biggest interest from a commercial point of view as well: the main characteristics and registered performance for all the reviewed approaches are reported. Along this direction, an extensive search of used databases has been performed and thus made available to the research community.**

I. Introduction

In the last years, the rapid spread and exploitation of renewable energy resources, such as photovoltaic, resulted in big efforts in the scientific community from a multidisciplinary perspective. The Smart Grid paradigm has been advanced and it is now a reality in most countries worldwide. One of the key concept in Smart Grid studies is represented by *metering*, i.e. the capability of measuring the amount of a certain resource, available at a specific grid point. It is of fundamental importance since it allows to obtain a comprehensive amount of data, also in real-time.

These data are useful to extract key information to infer knowledge about the status of the grid and therefore to maximize the quality of the service provided through the grid itself. Computational Intelligence techniques are often adopted on purpose, and several different solutions have been proposed in the literature so far. A first important distinction has to be done among the grid type and the utility service related to them: the three most relevant grid types are represented by electrical energy, water and natural gas.

Nowadays, the situation is surely mature in the electrical energy field [1]–[3], where several databases and computational intelligence approaches for diverse applications already exist. Conversely, the water and natural gas case studies seem to lack of appropriate databases and studies for the development and/or improvement of suitable computational intelligence techniques, with special reference to load forecasting and leakage detection applications, which can have an immediate impact on the quality of service provided by those grids. The water is a common good and it is important to preserve such valuable resource, at the basis of human life. Concerning the natural gas, the International Energy Outlook 2013 (IEO2013) [4] confirmed that, with an increase by $2,5\%$ per year, nuclear power and renewable energy are the world's fastest-growing energy sources. However, even now the natural gas remains an essential resource. Indeed, until 2040, the 80% of world energy will continue to be supplied by fossil fuels and, with an increase in global consumption of $1,7\%$ per year, natural gas is the fastest-growing fossil fuel in the outlook. Increasing supplies of tight gas, shale gas, and coalbed methane support growth in projected worldwide natural gas use.

In order to support research and propose more and more performing solutions in load forecasting and leakage detection for the smart water and gas grid case studies, it is undoubtedly relevant having a survey that can serve as useful starting point. This motivated the authors to produce the proposed survey, where a comprehensive collection of the recent state-of-the-art works and related databases, from 2009 to date, is presented. In addition to the scarcity of studies on both smart water and gas grid, especially if compared with the electrical energy case study, the two grids have been jointly addressed because it is believed that achievements in each field can easily cross-fertilize the other. This issue is surely enhanced by the similar characteristics of the grids themselves and related common nature of metering devices used in both grids.

One of the most relevant result of this overview, is represented by the dearth of suitable databases in the literature, which acts as a serious bottleneck for the development of innovative computational intelligence techniques and approaches for load forecasting and leakage detection. Indeed, as it will be clearer later on, some of the databases show short data recording period or very low sample rate, and most are unfortunately unavailable, being therefore not useful for scientific exploitation. This yields to the presence of non-standard evaluation criteria and the inability to perform a comparison between different approaches, since each new method has been tested with a different database.

This is the paper outline. In Section II an overview of the published databases for water and natural gas is presented pointing out the different aspects. Section III presents the state-of-the-art load forecasting techniques for both water and natural gas grids, whereas in Section IV non-intrusive leakage detection techniques are described. Section V concludes the paper.

II. Databases

In this section, the published state-of-the-art databases are reported. Table I reports the resource type, the reference period

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TABLE I. SUMMARY OF THE DATASETS FOR WATER (W) AND NATURAL GAS (G) IN THE STATE OF THE ART.

Contr.	Res.	Time Period	Samples	Availability
[5]	W	–	–	not public
[6]	W	35,000 days	–	not public
[7]	W&G	Apr 2012 – Mar 2013	$524\,k$*	**publicly avail.**
[8]	W	2006 – 2011	$210,336$	not public
[9]	W	11 Nov – 22 Dec, 2012	–	not public
[10]	W	Apr – Jul, 2010	–	not public
[11]	W	May 1992 – Dec 2002	125	**publicly avail.**
[12]	W	1990 – 2000	10	not public
[13]	W	1991 – 2003	$\sim 4,380$	not public
[14]	G	Mar 2001 – Aug 2005	$\sim 1,611$	not public
[15]	G	Jun 1996 – Mar 2012	$\sim 5,752$	not public

*: samples for each measured resource.

of the data collected, the number of data samples and the database public availability for each contribution. The authors have contacted researchers responsible for the databases creation and maintenance, in order to receive further information about the collected data and their public availability.

To evaluate two fault diagnosis approaches, Quevedo *et al.* [5] used the data acquired from the Barcelona water transport network. The database is composed of the received real-time data from 200 control points, which mainly include flow meters and also some pressure sensors. No further information have been provided by the authors and the database is not publicly available.

In the study proposed by Cardell-Oliver [6], the water consumption data have been collected by a wireless sensor network. The network reaches about $11,000$ smart meters (one per household) and the database consists of some selected information over $35,000$ days. Unfortunately, the database is not publicly available, nor is it likely to be released, as confirmed by the author.

Makonin *et al.* [7] presented AMPds (Almanac of Minutely Power dataset), "a dataset that contains detailed measurements not seen in other databases". The dataset is composed of power, water and natural gas meter data. The energy consumption of a single house has been recorded using 21 sub-meters for an entire year (from April 1, 2012 to March 31, 2013) at one minute read intervals. In detail, for natural gas metering there were two meters: the whole-house meter (WHG) and the gas furnace meter (FRG). For the water metering there were also two meters: the whole-house meter (WHW) and the hot water meter (HTW). Nevertheless, being the dataset composed of values recorded from a single residence, it is not suitable for load forecasting and leakage detection purposes.

Bakker *et al.* [8] tested their forecasting method on a database composed of the water demand, over 6 years, of several areas in the Southern region of The Netherlands. The reference period goes from 2006 to 2011 with a 15-min time step in m^3/h, i.e. a total of $210,336$ values. For these reasons, the database is really suitable for research purposes, but it is not publicly available.

Boracchi *et al.* [9] used flow and pressure data collected in two inlets as well as five pressure values, measured by monitoring sensors right inside the pipelines. The information have been recorded from 11^{th} November to 22^{nd} December 2012. The authors have not requested the database since the recorded period is too short to test a forecasting system.

Zhu and Xu [10] tested their forecasting approach using the urban water consumption from April to July, 2010, of a Chinese city. Unfortunately, no further information have been provided.

Data on the daily water consumption of Tehran, from 1991 to 2003, have been used by Tabesh and Dini [13]. Presently, the database provided by the Tehran Water and Wastewater Company is not publicly available and no additional information have been supplied.

The dataset used by Nasseri *et al.* [11] is available and it is composed of the monthly water demand of Tehran, from May 1992 to December 2002.

Liu and Chang [12] have employed the annual water demand from 1990 to 2000, including urban domestic water, rural domestic water, industrial water and agricultural water. Despite presenting a wide time interval, both databases ([11], [12]) have been created from data collected over 10 years, but a monthly or an annual water demand can not completely fulfill the needs for a research study in smart metering and load forecasting. For this reasons, no further information have been requested to the authors.

A suitable database of natural gas consumption has been used by Azari *et al.* [14]. The daily consumption of gas has been recorded from 21 March 2001 to 8 August 2005, for a total of 1611 collected data. So far, the database is not publicly available.

In the thesis by Pang [15], the tests have been executed using a dataset of daily natural gas demand from January 1996 to March 2012. The data have been supplied by the GasDay Lab at Marquette University, and, presently, are not publicly available.

III. LOAD FORECASTING

Nowadays, the estimation of the future demand of a specific resource is at the foundation of distribution systems. Improvements in forecast reliability result in designing more suitable network and in more efficient management decisions, thus reducing the wastes. In the following section the recent studies about the forecasting methods of demand and consumption of water and natural gas are reported. For each referred work, the main information are shown in Table II, such as the computational intelligence technique and the evaluation criteria adopted therein.

A. Water

Bakker *et al.* [8] realized a model that forecasts the short-term water demand. For each 15 minutes time step a new 48-h forecast is calculated moving forward the vector with forecasted water demand. The model uses three main phases to forecast the water demand: first of all, the average water demand for the next 48-h is forecasted; then, the normal water demand for each single 15-min time step is forecasted; finally, if applicable, extra sprinkle water for the individual 15-min time steps are forecasted. The datasets of water demand are collected over six different areas in the period 2006-2011. Each dataset consists of the demand per 15-min time step in m^3/h over a period of six years (210,336 values). The first year, 2006, has been used to adapt the model factors;

TABLE II. SUMMARY OF THE EXISTING CONTRIBUTIONS IN THE STATE OF THE ART AND THEIR RELATIVE PERFORMANCE.

Contr.	Res.	Technique	Evaluation Criteria	Performance
[8]*	W	Adaptive	MAPE - RRMSE - R^2	$1.44, \%5.12\% - 2.01\%, 8.21\% - 0.658, 0.803$
[8]**	W	Adaptive	MAPE - RRMSE - R^2	$3.35\%, 10.44\% - 4.85\%, 16.71\% - 0.905, 0.987$
[10]	W	QPSO-RBF ANN	MSRE	2.14%
[11]	W	EKF-GP	NMSE - R^2	$0.23, 0.76$
[12]	W	GM(1,1)	Max RE - MRE	$-19.50\%, 13.85\%$
[12]	W	RBF ANN	Max RE - MRE	$2.29\%, 2.01\%$
[13]	W	Fuzzy (weather)	MSE - NMSE - R^2 - MAPE	$0.042, 0.465, 0.760, 7.63\%$
[13]	W	Neuro-Fuzzy (weather)	MSE - NMSE - R^2 - MAPE	$0.008, 0.069, 0.931, 2.85\%$
[14]$^+$	G	ANN	RE	$1.5\% - 6.8\%$
[14]$^{++}$	G	ANN	RE	$0.33\% - 1.86\%$
[15]	G	MWS	RMSE - MAPE - wMAPE	–

*: 24-h time step, **: 15-min time step, $^+$: daily prediction, $^{++}$: monthly prediction

the remaining years, 2007 to 2011, have been used to evaluate the approach. In Table II the maximum and minimum overall model performance are reported, given as relative error (RE), mean absolute percentage error (MAPE), relative root mean squared error (RRMSE) and determination coefficient (R^2), commonly known as Nash-Sutcliffe efficiency coefficient [16].

Zhu and Xu [10] combined quantum particle swarm optimization (QPSO) algorithm [17] with RBF neural network in order to develop a forecasting method for urban water consumption. RBF neural network is a forward neural network with three layers: input, hidden and output. The neural function is a radial basis function, defined as $R_i = \exp(- \parallel x - c_i \parallel^2 /2\sigma_i^2),\ i = 1, 2, \ldots L$. Here L is the number of hidden layer unit, c_i is the center of basis function, and σ is the width of gaussian function of the i-th hidden layer. Quantum particle swarm optimization algorithm integrates the improved quantum evolutionary algorithm (QEA) into the particle swarm optimization (PSO). The system performance has been evaluated on a database composed of water consumption and meteorological data from April 1 to July 10, 2010. The time range of Apr-June 2010 is used as training set to forecast the urban water consumption of July 1-10. The evaluation criteria are the relative error (RE) and the mean square relative error (MSRE); the achieved results are shown in Table II. Moreover, as compared with RBF and PSO-RBF neural networks, the experimental results have shown that the QPSO-RBF neural network achieves better performance in terms of both convergence speed and forecast accuracy.

Nasseri *et al.* [11] developed a hybrid model based on the combination of Genetic Programming (GP) and Extended Kalman Filter (EKF) to predict the monthly water demand in Tehran. To reveal the ineffective parameters during the mathematical modeling, the finalized GP formula is updated using the Mathematical Sensitivity Analysis (MSA). This screening leads to achieve the best formula possible with less mathematical complexity. The Extended Kalman Filter is applied to infer latent variables. The available dataset includes monthly water consumption in Tehran from 5/1992 to 12/2002. The system has been trained using 70% of the original dataset; the remaining data (30%) have been used for verification. The criteria used to evaluate the results are the normal mean square error (NMSE) and the determination coefficient (R^2). The obtained results are reported in Table II.

Liu and Chang [12] presented a comparative study between two forecasting models: the grey forecast GM(1,1) model and the RBF neural network model. In the former one, the model creates a function relationship, first-order linear dynamic, between water demand and time using the water demand of the past years to forecast the water demand in the future years. In the latter one, a 3-layer forwarding neural network has been used. The annual water demand data of Yangquan from 1990 to 1997 has been used as initial sequence. The resulting forecast model for the GM(1,1) is:

$$\hat{x}(k+1) = 415922.61 \exp(0.0518k) - 393339.77$$

where $\hat{x}(k+1)$ indicates the forecasted value for the sample $k+1$. For the neural network 13 water demand forecast factors as input have been selected, and the total annual water consumption is the output. The water demand in 1998-2000 has been used as validation data. The maximum relative error (Max RE) and the mean relative error (MRE) have been adopted as evaluation criteria between the approaches. The achieved results are reported in Table II.

Tabesh and Dini [13] modelled the short-term demand of water in Tehran using Sugeno fuzzy and neuro-fuzzy inference system (ANFIS). The dataset is composed of water data consumption and meteorological data, and the system has been developed using three different model of data partitioning: two random and one non-random approaches. In any kind of approach, the 60% of the set has been used for training, the 15% for validation and the remaining 25% for testing. In the non-random approach the set has been partitioned according to the time progression, whereas a random selection has been used for the others approaches. The used meteorological data were the daily average temperature and the relative humidity. The results have been evaluated using the mean square error (MSE), the normal mean square error (NMSE), the correlation coefficient (R^2) and the mean absolute percentage error (MAPE). In the fuzzy approach the best data have been obtained by the model that includes the last year water consumption, with a MSE of 0.042, a NMSE of 0.465, a R^2 of 0.760 and a MAPE of 7.63%. In the neuro-fuzzy approach, the best performance have been obtained for three different combinations. The first model includes the last day, the last week and last year consumption. The second one contains all the single last week days consumption, and the last week consumption. The third one includes the same values of the previous model with the addition of the last years consumption. The MSE values are included within $0.007-0.009$, the NMSE within $0.064 - 0.074$, the R^2 within $0.926 - 0.936$ and the MAPE within $2.83\% - 2.87\%$.

B. Gas

In order to predict the daily and monthly gas load consumption, Azari *et al.* [14] used an approach based on artificial neural networks. For the daily gas load consumption, an artificial neural network with two hidden layer and fifteen nodes in each hidden layer has been used. The input vector is composed of 29 elements: meteorological parameters, gas consumption data for the previous five days, and the meteorological parameters forecasting for prediction day. For the monthly gas load consumption, an artificial neural network with one hidden layer and seven nodes in the hidden layer has been used. The input vector is composed of 3 elements: monthly effective temperature for the previous and predicted month, and gas load consumption for the previous month. The daily gas consumption data as well as the meteorological data from 21 March, 2001 to 8 August, 2005, overall 1611 pieces of data, have been used to train the network and to evaluate the performance. 90% of the data are used for training, and the rest for validation. The obtained results are ported in Table II.

Pang [15] investigated the introduction of exogenous weather inputs in the original GasDay[1] forecast model. Using the proposed Multiple Weather Stations (MWS) model the accuracy of forecasts experiences a significant improvement. The introduction of new instruments has improved the forecast by capturing more characteristics for the model, with both heating and non-heating purposes. The MWS model had improvements in terms of root mean square error (RMSE), mean absolute percent error (MAPE) and weighted mean absolute percent error (wMAPE) in the “shoulder months” for all the testing data sets. Overall, the new model improved the RMSE by about 5% and improved the MAPE by about 4%, comparing to the existing method. For the winter months, the forecasting accuracy is very similar. In the “shoulder months” and summers, the MWS model is superior to the existing method on average by about 7% in terms of RMSE. The tests have been executed using time series data from January 1996 to March 2012, keeping the last year of data as testing set. The dataset has been provided by the GasDay Lab at Marquette University and the National Oceanic and Atmospheric Administration.

IV. Leakage Detection

As mentioned in Section I, the availability of suitable databases allows a faster progression for different aspects of load forecasting and leakage detection. Concerning the smart metering, the main aspect is the capability of analyzing the data collected by the monitoring sensors (i.e. wireless sensor network) and detecting unexpected events in the shorter possible time, namely leaks due to pipe breakage. Therefore, non-intrusive techniques, that use only the measurements provided by the sensors network, are reported in the following section.

A. Water

Whittle *et al.* [18] presented the WaterWise platform, wireless sensor network based, able to detect and localize leaks, and identify the areas of risk in the network. The platform is structured in three main layers: on-line wireless sensor network (WSN), Integrated Data and Electronic Alerts System (IDEAS), and Decision Support Tool Modules (DSTM). The sensors provide both hydraulic parameters (pressure, flow, hydrophone) and water quality information (pH, conductivity, temperature). The data from the WSN are collected and specific analysis can be executed, such as forecasting the water demand. The main aspect proposed by WaterWise is the detection and localization of leaks or bursts, analyzing the pressure transients [19]. To detect the transient event the system uses two approaches: wavelet decomposition or time-domain statistical analysis. The localization is performed by a graph-based search algorithm. The methods for non-intrusive detecting and locating transient pipe burst events have been presented by Srirangarajan *et al.* [19]. Transient in real-time pressure measurement gives the ability to detect events such as leaks, pipe burst and system operations (such as valve opening/closing). The authors applied a multiscale wavelet analysis, both wavelet coefficients and Lipschitz exponents, that provides additional information about the nature of the signal feature detected, and can be used for feature classification. The time information about the arrival time of the pressure drop in different measurement points allows to estimate the location of the burst, in combination with a graph-based localization technique. The algorithm has shown good performance in leakage detection, and presented an average localization error of $37,5\,m$.

Boracchi *et al.* [9] proposed a combination of two change-point methods to detect the time instant when leakage occurs. At first, the minimum night flow is analyzed to obtain an estimation of the started day. Then, the exact time when the leakage has occurred is obtained using the information about pressure measurements and network model. The proposed method avoids the approximation of the pressure measurements over a large time interval. The method has been tested using real data collected from 11^{th} November to 22^{nd} December 2012 of a big European city. The data have been measured by two inlets where flow and pressure are measured as well as five pressure monitoring sensors right inside. The tests have been executed with both artificially induced leakages and real leakages.

In order to detect meaningful activities from the real-word smart metering, Cardell-Oliver [6] presented a new approach. Using automatic collected measurement, selected from a network of over 11,000 smart meters over 35,000 days, the method is able to identify activities extracting useful features. A new unsupervised learning method has been proposed, which combines rule-based activity labels and k-means clustering. The recognized activity classes are defined by a subset of logic rules that characterized the set of days on which an activity occurs. The activity classes are: *empty days*, *continuous days*, *peak days* and *normal days*. In addition, clustering is adopted to verify that the category of *normal days* does not conceal other activities.

Fuzzy Inductive Reasoning (FIR) has been applied, by Sanz *et al.* [20], to detect and localize leak in the water network. The approach uses the pressure values provided by two sensors, located in two different areas of the District Metered Area, Nova Icària, in Barcelona. Fuzzification, qualitative modeling, qualitative simulation and defuzzification are the four main stages of the proposed method. Using simulated data the fuzzy models for leakages and non-faulty scenarios are created. Each

[1] http://www.gasday.com/web/

model is compared with the real data and the best one is chosen. The proposed approach isolates correctly the leakages and presents a good precision, better than achieved by Quevedo *et al.* [21].

A correct pressure management in water distribution networks can help to reduce leakages and pipe breaks due to sections at high pressure. Nicolini [22] presented a method based on genetic algorithms (GA) in order to minimize both pressure reducing valves (PRVs) and water losses. The method addresses the problem using a single-object GA first, for model calibration, and then a non-dominated sorting GA for optimization. The approach has been evaluated on a real distribution network with remarkable results.

B. Gas

Murvay and Silea [23] realized a survey of the state-of-the-art gas leakage detection and localization techniques. All the possible approaches are reported, but only the approaches that can be used in the automatic monitoring scenario are described below.

A first method of non-intrusive leakage detection is based on the *negative pressure wave*. When a leak is present in a pipeline a pressure wave is generated, from the location of the leakage point, and propagates both upstream and down stream [24]. This wave is called rarefaction or negative pressure wave and can be measured by pressure transducer. By analyzing the collected pressure measurements, for example using a support vector machine approach [25], the leakage can be detected. Moreover, comparing the arrival times of the pressure wave to the two opposite transducers, referring to the leak position, the location of the leak can be easily identified. If a transducer is closer to the leak, then it receives the pressure wave before the other, and can be used to detect the leak location with good precision.

A fast leakage detection method is the Pressure Point Analysis (PPA$^{\text{TM}}$) [26]. The approach is based on the principle that the pressure inside pipeline drops if a leak occurs. Continuous measurement of the pressure in different points along the pipeline are required for this technique. These measurements are used to compute, by means of statistical analysis, a threshold. When the mean value of the pressure measurements decreases under this thresholds, the presence of a leak will be declared.

Gas leaks can also be detected using statistical analysis, without the need of a mathematical model. Working with multiple sensors along the pipeline that measure pressure and flow, the system generates a leak alarm only in case of anomalous changes in the encountered pattern. Zhang and Di Mauro [27] improved the methods introducing leak threshold, which is set after a tuning period. During this period, there must be no leaks and the parameter variance has to be analyzed for different operating conditions. This tuning process needs to be done over a long period of time and it is required in order to reduce false alarms. The presence of a leak during the tuning period will affect the initial condition and the erroneous behaviour will be considered as normal. Only if the leak grows in size enough to go beyond the set threshold, then it will be detected.

V. Conclusion

The authors collected the state of the art of databases and computational intelligence techniques (specifically load forecasting and leakage detection) for water and natural gas. As shown in Table I, further information have been requested, for both the gathered data in the database (e.g. sample rate and type) and the database availability. Regarding the databases, the survey highlights two shortcomings: they either have limited availability or lack of appropriate data. For example, the database presented by Makonin *et al.* [7] is available and has a good reading time interval, 1 minute, of both water and gas demand. But it refers to measurement in a single house. In contrast, the database proposed by Bakker *et al.* [8] presents both a good reading time interval and appropriate data, but the database is not publicly available yet. Furthermore, it is difficult to make an objective comparison between the methods presented in Section III. Firstly, the approaches have to be tested using a common database. Secondly, for both water and gas references, as shown in Table II, there is a significant dissimilarity between the adopted evaluation criteria.

The authors are confident that the spread of innovative monitoring systems, which are more and more often based on low-power wireless devices [28] [29], will ensure a facilitation for collecting large amount of data, as partially shown in [6], and creating suitable and publicly available databases. This will enable a fair and comprehensive evaluation of already proposed computational intelligence solutions for smart water and gas grids, as well as the development of new ideas from the research community.

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