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A NEURAL DATA-DRIVEN ALGORITHM FOR SMART SAMPLING

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ABSTRACT

Wireless sensor network (WSN) have gained much more attention from researchers. WSN makes the use of sensor nodes generally battery-operated .Their prevalence is threatened by a number of technical difficulties, especially the shortage of energy. To overcome this problem, we propose a smart reduction in data communication by sensors. In order to reduce the measurements, we present a data prediction method based on neural networks which performs an adaptive, data-driven, and non-uniform sampling. Evidently, the amount of possible reduction in required samples is bounded by the extent to which the sensed data is stationary. The proposed method is validated on simulated and experimental data. The results show that it leads to a considerable reduction of the number of samples required (and hence also a power saving) while still providing a good approximation of the data.

KEYWORDS: Data-driven sampling, Energy consumption, Neural data prediction, Sensor networks

INTRODUCTION

Wireless sensor networks (WSN) have received a great attention in recent years. They have a wide variety of applications such as event detection, target tracking, environment sensing, elder people monitoring, and security[1-8].A wireless sensor network consists of sensor nodes deployed over a geographical area for monitoring physical phenomena like temperature, humidity, vibrations, seismic events, and so on [9].

A WSN is usually made up of a large number of sensors that communicate their sensed information to other nodes. Typically, a sensor node is a tiny device that includes three basic components: a sensing subsystem for data acquisition from the physical surrounding environment, a processing subsystem for local data processing and storage, and a wireless communication subsystem for data transmission. In addition, a power source supplies the energy needed by the device to perform the programmed task. This power source often consists of a battery with a limited energy budget. In addition, it could be impossible or inconvenient to recharge the battery, because nodes may be deployed in a hostile or unpractical environment. On the other hand, the sensor network should have a lifetime long enough to fulfil the application requirements. In many cases a lifetime in the order of several months, or even years, may be required. Therefore, the question is: "how to extend the network lifetime for long time?" In some cases it is possible to scavenge energy from the external environment [10] (e.g., by using solar cells as power source). However, external power supply sources often exhibit a non-continuous behaviour so that an energy buffer (a battery) is needed as well. In any case, energy is a very critical resource and must be used very sparingly. Therefore, energy conservation is a key issue in the design of systems based on wireless sensor networks. In this paper, data prediction is employed [13, 14]. Sensors are often supplied with scarce energy resources. Hence, energy saving is crucial to the operation of WSNs, and devising methods for efficient power consumption is central to the research in this area.
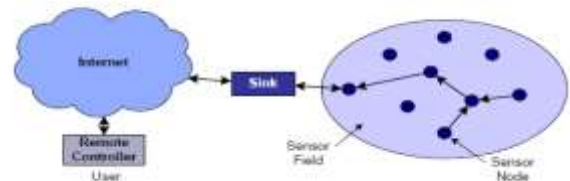

Fig 1. Sensor Network Architechture

ENERGY CONSTRAINTS

Energy is required in every mini or major operation of any type of application. . Sensors are equipped with batteries, but these batteries do have a limited life time, e.g. in underwater scenario, there are no plug-in sockets to provide the power as per the requirement. Sensors has scarce energy resources and hence energy saving is crucial for operation. Energy-Efficient networking protocols and devising method for efficient power consumption are required now days. The communication subsystem has a much higher energy consumption than the computation subsystem. It has been shown that transmitting one bit may consume as much as executing a few thousands instructions. Therefore, communication should be traded for computation. The radio energy consumption is of the same order in the reception, transmission, and idle states, while the power consumption drops of at least one order of magnitude in the sleep state. Therefore, the radio should be put to sleep (or turned off) whenever possible. Depending on the specific application, the sensing subsystem might be another significant source of energy consumption, so its power consumption has to be reduced as well [11].

ENERGY CONSERVATION SCHEMES

Many approaches were proposed to reduce the power consumption of a sensor network, but three main techniques are the most important among them duty cycling, data-driven approaches, and mobility [12]. Since duty cycling patterns are unaware of data which are gathered from sensor nodes, data-driven approaches are more appropriate to reduce the energy consumption of the WSNs. The microcontroller can switch on the sensors only during the measurement, reducing the power consumption [4, 5].

Nevertheless, unneeded communications could sporadically happen because of transferring unnecessary data. Reducing extra communications is a way to save energy which can be followed by data-driven techniques. While 'energy-efficient data acquisition' schemes are mainly concerned with decreasing power consumption relevant to the sensing subsystem, 'data reduction' schemes focus on unneeded samples.

PROPOSED METHOD

In this paper an innovative method is proposed and the same is tested on simulated and experimental data. A neural algorithm is considered to forecast sensor measurements .The uncertainties in sensor measurement allow the system to reduce Communications and transmitted data. A multilayer perceptron (MLP) [15] network is used. The central control unit of MLP decides when and from which sensor to acquire a new sample, without scheduling a periodical sampling. In order to save energy there is no transition in the period between two acquisitions.

METHODS

Algorithm for efficient sampling

The main aim of neural algorithm is to reduce the number of acquired data. Instead of acquiring we predicted them and estimated the uncertainty of the prediction. But when the associated uncertainty increases above a threshold level an additional measurement was required from a sensor. Each available measurement along with its uncertainty was considered together, assumed to be equal to the accuracy of the sensor. A MLP periodically performs a forward prediction on 100 realizations of stochastic inputs extracted from a uniform probability distribution with mean and range given by the available data and their uncertainty, respectively. The prediction was computed as the mean of the obtained 100 estimations. The uncertainty of the prediction U was defined in terms of two contributions U1 and U2. The first contribution U1 was the dispersion of the predictions, and defined as the range of the estimations provided by the MLP from the 100 random trials. The second contribution U2 was the estimated rate of prediction error:

$$U_2 = \frac{1}{2}\left(\frac{|p_j - m_j|}{\tau_j - \tau_{j-1}} + \frac{|p_{j-1} - m_{j-1}|}{\tau_{j-1} - \tau_{j-2}}\right) \qquad (1)$$

Where pj indicate the jth predicted value and mj indicate measured value, respectively (so that |pj −mj| is the prediction error), τ_j is the time sample in which the jth measurement is taken (so that $\tau_j - \tau_{j-1}$ is the time delay between the jth and the previous measurement). Thus, U2 is the mean of the last two estimated ratios between the prediction error and the time delay from the last measurement . The uncertainty U is defined as convex combination of the two contributions.

$$U = \alpha U_1 + (1 - \alpha)U_2 \qquad (2)$$

Where the parameter α (with 0 < α < 1) weights the importance of U1 and U2. When the same algorithm is tested on different datasets. α is considered 0.5 in the following. For specific applications, a different weight could be considered. When the uncertainty of the predicted measurement was larger than a threshold (chosen as sensor specific) a new acquisition was required from a sensor. Thus, the MLP was used to estimate when and from which sensor to acquire a measurement. This helps to reduce the number of measurements and, consequently, also the power consumption. Once the measurement are acquired from a sensor, with the help of interpolating method,

its present and past data were updated and the acquired measurements and their uncertainties were updated according to the sensor accuracy.

Data test bed
Simulated and experimental data were used to test the algorithm.

Simulated data
Simulated data are normally considered to be noise free and deterministic. Two different simulations are considered. The first one consist the following two signals

$x_1 (t) = \sin (2\Pi f(t)t)$

$x_2(t)=a(t)x_1(t)$ (3)

where t is the time (0 to 200 s range, sampled at 20 Hz), f(t) is a square wave varying between 0.5 and 1.0 Hz with period 20 s and $a(t) = 4 + \sin(0.15\pi t)$.Signal were quantized, in order to have resolution 0.05 . The x1 signal and x2 signal are first used separately, then together. In second set of simulations, two uncorrelated signals are taken and sampled every 0.1 s for 60 min.

In Chaotic regime [16] the sinusoid signal with frequency 0.1 Hz is first signal, and the second is defined as the first component y_1 of the solution [y_1 y_2 y_3] of a Lorenz system.

$$\begin{cases} \frac{dy_1}{dt} = -10(y_1 - y_2) \\ \frac{dy_2}{dt} = 28y_1 - y_2 - y_1y_3 \\ \frac{dy_3}{dt} = y_1y_2 - \frac{8}{3}y_3 \end{cases} \qquad (4)$$

Experimental data
Even for performing experimental data two different data are considered. The first dataset constituted of meteorological data from four sensors acquired every 15 min. The sensors measures temperature, pressure, wind velocity, and humidity, located at the Turin-Caselle airport, for 100 days from June to August 2010[17].The second dataset, temperature and humidity was gathered from two sensors of a Bluetooth-based acquisition system . The structure of the WSN is shown in Figure 1. A smartphone was used to communicate with sensors and reads data from them separately. The Free2Move Bluetooth module F2M03GLA was attached to the device. When the device is waiting for connection it consumes about 44 mW and 108 mW during the transmission. By Bluetooth module data is received from the UART interface of the microcontroller and forwards it to a receiver using the serial port profile (SPP) service. The device is operated by a 3-V lithium battery (CR2247 from Motorola) with 1,000 mAh. The sensors were fixed on a carrier, and their location was changed frequently in three different locations in a laboratory: close to a cold or to a warm source and far from heat sources. The sources were sufficient to prompt changes on temperature and humidity up to 5°C and 10%, respectively. Every 15s data were recorded for about an hour.
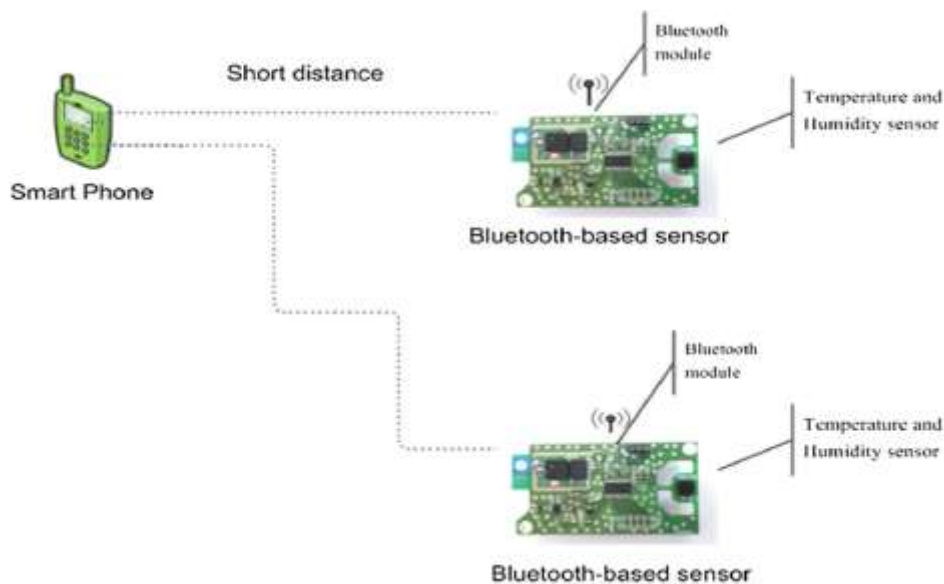

Fig 4. Bluetooth-Based Acquisition System of the Environmental Data Using a Smartphone
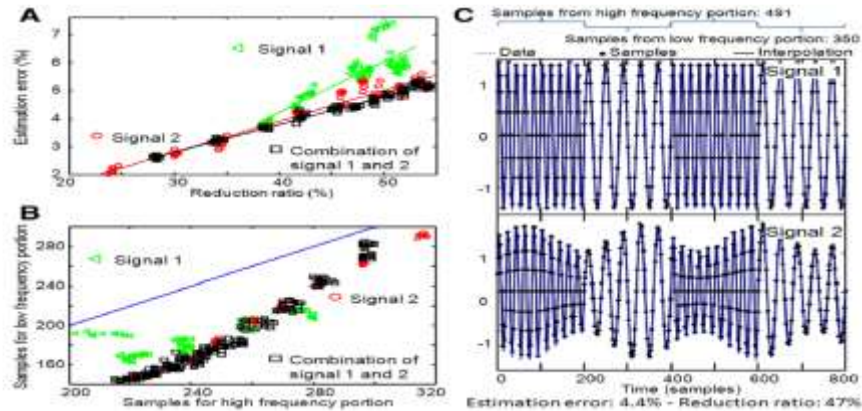
RESULTS AND DISCUSSION

Fig 5. Application of the Method to Non-stationary, Correlated signals . (A) Relation between reduction ratio and error (100 simulations with different thresholds are considered). (B) Samples for the portions of the signals with higher frequency versus those with lower frequency (same 100 simulations as in A). (C) Representative example application for the method.
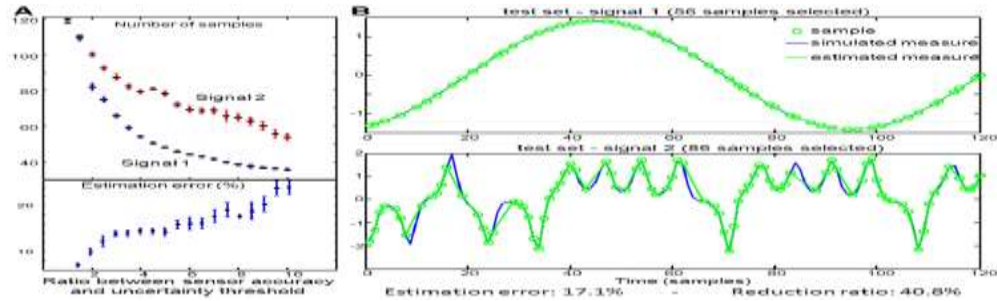

Fig 6. Application of the Algorithm to Simulated Data. (A) Number of samples and mean estimation error (mean and standard deviation over ten repetitions). (B) Representative example (threshold = 0.03 for both signals
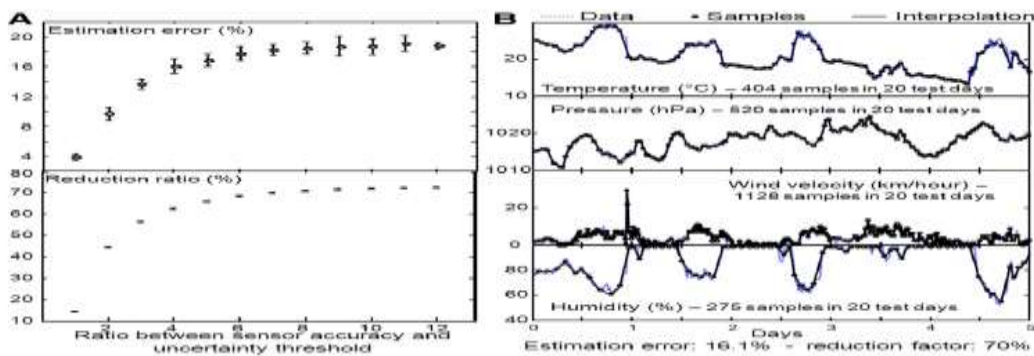

Fig 7. Application of the algorithm to meteorological experiments. Accuracy is assumed to be 0.2°C, 20 hPa, 0.1 km/h, and 1%, for the temperature, pressure, wind velocity, and humidity sensors, respectively. (A) Root mean square estimation error and reduction ratio as functions of the uncertainty threshold (20 repetitions are considered). (B) Example of application to a portion of the test set.
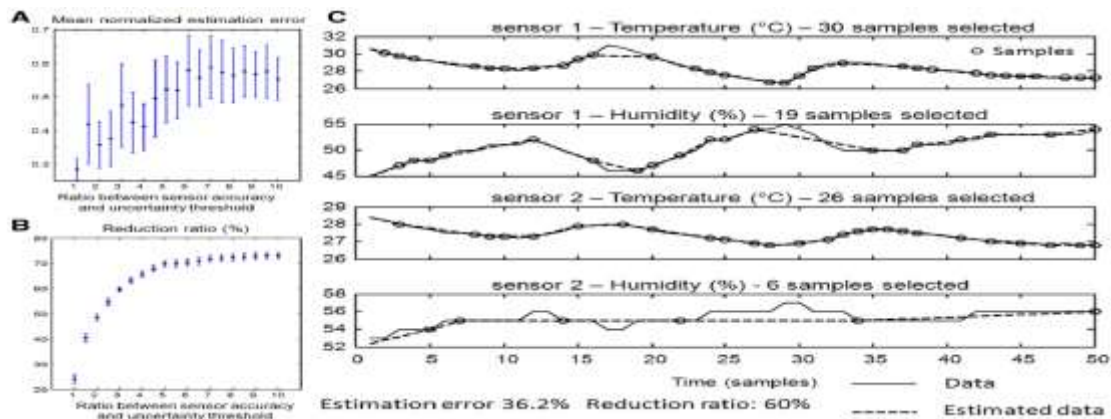
Fig 8. Application of the Algorithm to Indoor Experiments. (A) Root mean square (RMS) estimation error, and (B) reduction ratio as functions of the uncertainty threshold (assumed proportional to sensor accuracy; the method was run 100 times for each choice of the threshold, mean and standard deviations are shown). The accuracy was assumed to be 0.1°C and 0.3%, for the T and H sensors, respectively. (C) Representative example application for our method: uncertainty of the measurements was assumed to be two times the accuracy.

Fig 5 and 6 show the application of the method to simulated signals. In Figure 5, consist of correlated non-stationary signals . Panel A shows, the method using the combination of the two signals has a lower slope of the reduction ratio versus estimation error. This gives higher performances when information is jointly extracted from the two correlated signals. But this method selects more samples for the portions of the signals with higher frequency as shown in Fig 5B, the ability to adapt in time to temporal variations of the signal. In Fig 6, the chaotic and the sinusoidal signals are considered. Prediction of the sinusoid signal is simpler than that of the chaotic signal; thus the algorithm select more measurement to sample appropriately the second signal (in panel A). In Fig 7, a representative example application for our algorithm to our first bunch of experimental data is shown (meteorological data). The MLP used was trained and validated on the basis of the first 80 days. Then, it was applied on the following test set 20 days considered in Fig 7. Panel A shows, the results of many applications of the prediction algorithm to the test experimental data, with different thresholds. As expected, increase in threshold, increases the reduction factor, at the expense of decreasing the accuracy in estimating the measurements. Panel B shows, a portion of the test data. Wind velocity sensors requires more number of samples among the four sensors, reflecting the erratic dynamics of the signal. Whereas, the sampling of humidity has smooth variations correlated with temperature and has the lowest rate. The second bunch of experimental data used as an example application for our algorithm is shown in Fig7 (indoor experiment with a WSN). Humidity and temperature values are clearly correlated when measured from the same

sensor. Figure 7 shows the results of many applications of the prediction algorithm to the test experimental data with different thresholds. Again, by increasing the threshold, the reduction factor increases and the accuracy in estimating the measurements decreases. This paper proposes the possibility of reducing the amount of communications and the power consumption of a sensor network by a smart sampling of data. Since implementing Bluetooth-based acquisition system is the most expensive task in terms of power consumption in WSNs, energy saving can be obtained by timely replacing read data with predicted data. In a network, by reducing the number of measurements save lots of power or memory. To determine when and which sensor to interrogate an innovative and general method is discussed based on a data prediction approach. Data prediction is also applied [18] where data are predicted and streamed only when the mismatch with respect to the acquired measurement is higher than a threshold. Even Kalman filter is used in [19] for prediction with similar approach. On other hand base station is used in [20] to perform prediction instead of nodes. Another method to reduce power consumption in wireless sensor network is data aggregation [21].

The proposed neural algorithm estimates a prediction uncertainty for each sensor in the network during the monitoring. A particular sensor is interrogated when its uncertainty is above a threshold, which can be selected by the user. The algorithm to estimate the sensor uncertainties is based on a tool for data forecasting. It is used to estimate the rate of increasing of the prediction error and the future dispersion of the predictions due to the uncertainty contained in the available data. Two contributions related to the

predicted errors and to the dispersion of the predictions are given the same weight and linearly combined for the estimation of the uncertainty associated to the sensor.

The method was implemented and tested on both simulated and experimental data. Simulated data were examined to analyse the algorithm correctness. Moreover, when applied to two correlated signals, the method improved the performances with respect to the case in which it was applied on the two signals separately. Finally, the method required more samples to describe a chaotic system than a simple periodic one. All these results are in line with our expectations and confirm the reliability of the proposed method. When applied to meteorological data, the method was able to reduce the number of acquired samples with low estimation errors. More samples were recorded from the sensor monitoring the wind velocity, which provided a very erratic signal, with respect to temperature, pressure, and humidity, which showed regular and correlated variations. Notice that only a representative application is here considered: for practical applications, as only average information on wind velocity is usually of interest, subsequent measured or estimated samples could be averaged, reducing further the data to be effectively transmitted. The result of our method to indoor environmental data and outdoor application is in line. By observing the power consumed by the sensors during transmission and when in the idle state, some considerations could be made on the power that could be saved using our algorithm to reduce the number of measurements. Considering the indoor application, a reduction of the 50% of samples (getting an estimation error of about 35%, see Fig 8) allows to decrease the power consumption of about 7.5%; for the outdoor application here considered, data could be reduced to 70% (guaranteeing an estimation error lower than 20%, see Figure 7); thus, by scaling the acquisition and sampling times, a 10% of power saving could be obtained.

The results of the application of our method appear to be promising, even if a basic and general method was considered. Following the same ideas, more sophisticated methods could be developed, in order to better fit specific applications. For example, only the last two (measured or predicted) samples are here considered as the inputs of the prediction algorithm. This choice is due to the general applications discussed here, where four different datasets were processed by the same algorithm. However, different inputs can be chosen (e.g., the average values of data on long periods, often used in meteorological forecasting applications, or delayed samples with an optimally chosen delay, or simply more than two values could be used from each sensor; the methods of time series embedding [22] could be used to support a proper selection of the optimal delay and of the number of delayed values to characterize better each sensor). Moreover, a simple MLP was used for data prediction. Different alternative methods could be applied instead but still following the main general ideas of this paper. For example, different neural networks or fuzzy rule-based systems can be used [23]. Also, a single MLP is used here to predict all the measurements of the sensors, but different MLPs could be used, one for each sensor. The method estimates the uncertainty of the predicted measurements as the average of two contributions: different combinations can fit specific applications better. Moreover, a linear increase of the prediction error, including a memory term, is here assumed, but a more sophisticated (nonlinear, adaptive) algorithm can be introduced in the future to estimate better the raise of the prediction error in time.

CONCLUSION

This proposed method to make a smart sampling from sensors, in order to avoid unneeded measurements and, consequently, to reduce power consumption. In future different variants can be proposed to fit specific applications.

REFERENCES

1. RI Da Silva, V Del Duca Almeida, AM Poersch, JMS Nogueira, Wireless sensor network for disaster management, in IEEE Network Operations and Management Symposium: 19-23 Apr 2010 (Piscatway: IEEE, Osaka, 2010), pp. 870–873
2. D Wu, H Wang, Video surveillance over wireless sensor and actuator networks using active cameras. IEEE Trans. Automat. Contr. 56(10), 2467–2472 (2011)
3. S Kim, E Paulos, Air: sharing indoor air quality measurements and visualizations, in Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (ACM, New York, 2010), pp. 1861–1870
4. S Aram, A Troiano, E Pasero, Environment sensing using smartphone, in IEEE Sensors Applications Symposium (SAS): 7-9 Feb 2010; Brescia (IEEE, Piscataway,2012), pp. 1–4
5. S Aram, A Troiano, F Rugiano, E Pasero, Low power and bluetooth-based wireless sensor network for environmental sensing using smartphones, in Artificial Intelligence

Applications and Innovations (Springer, Heidelberg,2012), pp. 332–340

6. J Goldman, K Shilton, J Burke, D Estrin, M Hansen, N Ramanathan, R West, Participatory Sensing: A Citizen-Powered Approach to Illuminating the Patterns that Shape our World

7. A Chehri, P Fortier, PM Tardif, Security monitoring using wireless sensor networks, in Proceedings of Communication Networks and Services Research:14-17 May 2007; Frederlcton (IEEE, Piscataway), pp. 13–17

8. S Aram, A Troiano, F Rugiano, E Pasero, Mobile environmental sensing using smartphones, in Eren, H. and Webster, J., Measurement, Instrumentation, and Sensors Handbook, Second Edition: Electromagnetic, Optical, Radiation, Chemical, and Biomedical, Measurement. Boca Raton, FL: CRC Press, ch. 73, February 2014.

9. M. Ilyas and I. Mahgoub "Handbook of Sensor Networks: Compact Wireless and Wired Sensing Systems," Proceedings of the CRC Press, 2005.

10. IEEE Pervasive Computing, "Energy Harvesting and Conservation", Vol. 4, Issue 1, Jan-Mar. 2005

11. G Anastasi, M Conti, M Di Francesco, A Passarella, Energy conservation in wireless sensor networks: a survey. Ad Hoc Networks 7(3), 537–568 (2009) 12.

12. HY Shwe, XH Jiang, S Horiguchi, Energy saving in wireless sensor networks. J. Commun. Comput. 6(5), 20–28 (2009)

13. S Aram, L Mesin, E Pasero, Improving lifetime in wireless sensor networks using neural data prediction, in 2014 World Symposium on Computer Applications & Research - IEEE International Conference on Information and Intelligent Systems:18-20 Jan 2014; Sousse (IEEE, piscataway, 2014)

14. S Aram, L Mesin, E Pasero, A neural data-driven approach to increase wireless sensor networks' lifetime, in 2014 World Symposium on Computer Applications & Research – IEEE International Conference on

Artificial Intelligence:18-20 Jan 2014; Sousse (IEEE, Piscataway, 2014)

15. B Etienne, Optimization for training neural nets. IEEE Trans. Neural. Netw 3(2), 232–240 (1992)

16. L Edward, Deterministic nonperiodic flow. J. Atmos. Sci 20(2), 130–141 (1963)

17. A Troiano, E Pasero, L Mesin, In the field application of a new sensor for monitoring road and runway surfaces. Sensors & Transducers 10(2), 71–83 (2011)

18. V Kumar, BF Cooper, SB Navathe, Predictive filtering: a learning-based approach to data stream filtering, in Proceedings of the International Workshop Data Management for Sensor Networks (ACM, New York, 2004), pp. 17–23.

19. A Jain, EY Chang, YF Wang, Adaptive stream resource management using Kalman filters, in Proceedings of the 2004 ACM International Conference on Management of Data (SIGMOD2004) (ACM, New York, 2004), pp. 11–22

20. M Cordina, CJ Debono, Maximizing the lifetime of wireless sensor networks through intelligent clustering and data reduction techniques, in Proceedings of the 2009 IEEE Wireless Communication and Networking Conference: 5-8 Apr 2009; Budapest (IEEE, Piscataway, 2009), pp. 1–6

21. N Al-Karaki, R Ul-Mustafa, AE Kamal, Data aggregation in wireless sensor networks-exact and approximate algorithms, in IEEE Workshop on High Performance Switching and Routing (IEEE, Piscataway, 2004), pp. 241–245

22. H Kantz, T Schreiber, Nonlinear Time-series Analysis (Cambridge University Press, Cambridge, 1997)

23. B Meenakshi, P Anandhakumar, Optimization of energy consumption by fuzzy based routing in wireless sensor network. IOSR J. of Electronics and Commun. Engineering 2(1), 31–35 (2012)

24. H Simon, Neural Networks: A Comprehensive Foundation (Prentice Hall, Upper Saddle River, 1999)