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Energy rating of a water pumping station using multivariate analysis

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Abstract

Among water management policies, the preservation and the saving of energy demand in water supply and treatment systems play key roles. When focusing on energy, the customary metric to determine the performance of water supply systems is linked to the definition of component-based energy indicators. This approach is unfit to account for interactions occurring among system elements or between the system and its environment. On the other hand, the development of information technology has led to the availability of increasing large amount of data, typically gathered from distributed sensor networks in so-called smart grids. In this context, data intensive methodologies address the possibility of using complex network modeling approaches, and advocate the issues related to the interpretation and analysis of large amount of data produced by smart sensor networks.
In this perspective, the present work aims to use data intensive techniques in the energy analysis of a water management network. The purpose is to provide new metrics for the energy rating of the system and to be able to provide insights into the dynamics of its operations. The study applies neural network as a tool to predict energy demand, when using flowrate and vibration data as predictor variables.

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Keywords: water supply system; energy rating; energy efficiency; neural network

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1. Introduction

Water is a fundamental element for life but its scarcity is caused by a number of factors such as climate change, population growth, urbanization, agricultural and industrial activities. Global water withdrawals are projected to increase by 55% through 2050 due to growing demands from manufacturing (400%), thermal electricity generation (140%) and domestic use (130%). In addition, there is clear evidence that groundwater supplies are diminishing, with an estimated 20% of the world's aquifers [1]. Energy is required for two components of water provision: pumping and treatment (before and after use). In these applications, electricity costs are estimated to be responsible of a share ranging from 5% to 30% of the total operating cost of water and wastewater utilities, but in some developing countries such as India and Bangladesh, it is as high as 40% of the total operating cost [1]. It is therefore of the utmost importance to address the sustainability of water cycle from the viewpoint of both an efficient use of the resource, and the maintenance of high quality service standards. In this respect, water infrastructures require a profound transformation in terms of withdrawal, resilience and reliability.

The Water Supply System (WSS) consists of a series of operations based on the distribution of drinkable or treated water to end-users, as well as the collection and treatment of wastewater and their restitution into the environment.

In parallel to the preservation of water resources, the reduction of the energy flows involved in the process has to be taken into account also, by promoting the proper management of the energy use in the various operations required to guarantee the service. Water and energy flows represent the main resources involved in the WSS and as such they have to be preserved through sound management.

Specific Energy Performance Indicators (EnPI) have been defined for WSSs [2-4], most of them proposed by the International Water Association (IWA) [5]. In this number, customarily used metrics are the pumping capacity utilization, normalized energy demand, reactive energy demand and energy recovery [5].

In the energy rating of WSS issues can be correlated to: i) the correct selection of EnPI to account for the dependence from the observed (and monitored) process, and ii) the impossibility to describe the system dynamics using a single energy indicator at component of system levels [6, 7].

The energy behavior of WSS depends upon a large number of variables, even external to the process itself [8, 9] (e.g. amount of water source, seasonality, rainfall, and other environmental parameters). A simple indicator is not able to catch all these dependences. The analysis of these interconnections allows to achieve full understanding of the energy behavior; for this reason data intensive techniques prove to be a valuable tool.

Data intensive techniques consist of several disciplines, including statistics, data mining, machine learning, neural networks, social network analysis, signal processing, pattern recognition, optimization methods and visualization approaches. There are many specific techniques in these disciplines, and they overlap with each other [10]. Among these, Artificial Neural Network (ANN) has wide range of application coverage: pattern recognition, image analysis, adaptive control, and other areas. Research on neural-network-based control systems has received a significant consideration over the years. Many methods have been developed and successfully applied to real industrial processes [11, 12].

A neural network based control architecture is used to estimate the behavior of unknown nonlinear systems and the controller is then formulated using the estimation results. The estimation uses the measured inputs, the formulation of the control signal is then determined from the neural-network model, which approximates the system which is nonlinear with respect to its input arguments [13]. In particular, in many engineering problems, such as process controllers employing model predictive algorithms, it is essential that at any given time the process outputs will be predicted many time-steps into the future without the availability of output measurements in the horizon of interest. For this reason, in forecasting and in fault monitoring and diagnosis applications, the availability of accurate empirical models with multi-step-ahead (MS) predictive aptitudes are desirable [14, 15].

Among predictor design based on nonlinear model structures, Nonlinear Auto Regressive models with eXogenous input (NARX model) has proven to be successful in many applications [16], and more recently, has been proposed and extensively used in the identification and control of dynamic systems [17, 18].

This paper aims to define and apply new metrics for the energy rating of a water supply system. These metrics are defined employing data intensive tools, specifically the NARX neural network. NARX performs the forecasting of the energy demand providing a model for the energy behavior of the system. The deviation of the energy demand

from the model provides the metrics for the evaluation of energy performance. The proposed methodology was evaluated on a water supply system.

2. Methodology

2.1. NARX Neural Network

The Nonlinear Auto Regressive model with eXogenous input (NARX model), therefore called NARX recurrent neural networks [19, 20], is a powerful class of models which proven to be well suited for modeling non-linear systems and time series [21].

Two crucial qualities about NARX networks with gradient-descending learning gradient algorithm are: first, the learning is more effective than in other neural networks (the gradient descent is better in NARX), and second these networks converge much faster than other networks [19, 20]. The simulated results show that NARX networks are often much better at discovering long time dependences than conventional recurrent neural networks [21]. For instance, an explanation why output delays can help long-term dependences can be found by considering how gradients are calculated using the Back-Propagation-Through-Time (BPTT) algorithm [21].

The network used in this study to optimize the objective function is the Recurrent MultiLayer Perceptron (RMLP) network. The employed training configuration is the series-parallel implementation; where the output regressor is made only by effective output values of the system (open loop). On the other hand, for testing and multi-step-ahead prediction phases, the parallel mode configuration was employed; in this instance the estimated outputs are feedbacks and include the output regression (closed loop). Fig. 1 provides a representation of closed (Fig. 1(a)) loop and open loop (Fig. 1(b)) network architecture. The network hidden layer has ten nodes and time delay equal to two was chosen.

The equation describing the autoregressive model reads as:

$$y(n+1) = f[y(n),...,y(n-dy+1); x(n),x(n-1),...,x(n-dx+1)],$$

where x(n) and y(n) respectively represent the input and output of the model with discrete time step n, and $dx \geqslant 1$ and $dy \geqslant 1$, $dx \geqslant dy$, are the input and output memory.

In particular, the Bayesian Regularization algorithm was used as the training algorithm; it is a training network function that updates the weight and polarization values according to Levenberg-Marquardt optimization. It minimizes a combination of square and weights errors, and then determines the correct combination to produce a generalizing network. In this way, it is possible to get the increase in the accuracy of model parameters.

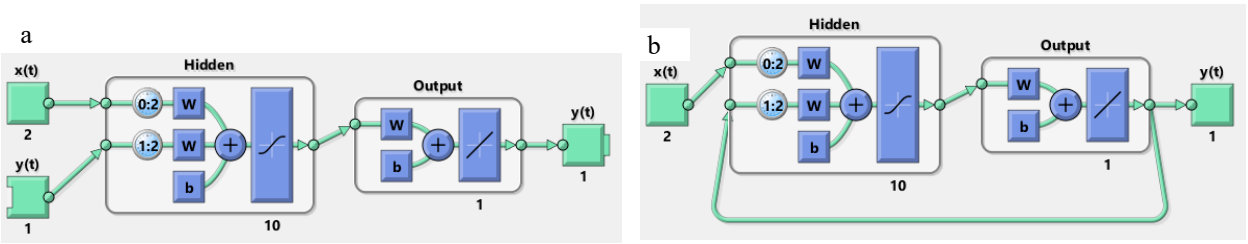

Fig. 1. Representation of (a) closed loop and (b) open loop network architecture.

3. Case Study

The work interested a water supply system located in Prossedi, province of Latina (Italy) and providing drinkable water to five towns, i.e. Priverno, Pisterzo, Prossedi, Roccagorga-Maenza and Villa S. Stefano. The system consists of two pumps for each town line, one of them for backup. Fig.2 shows the water supply system layout, displaying the pump size for each district supplied.

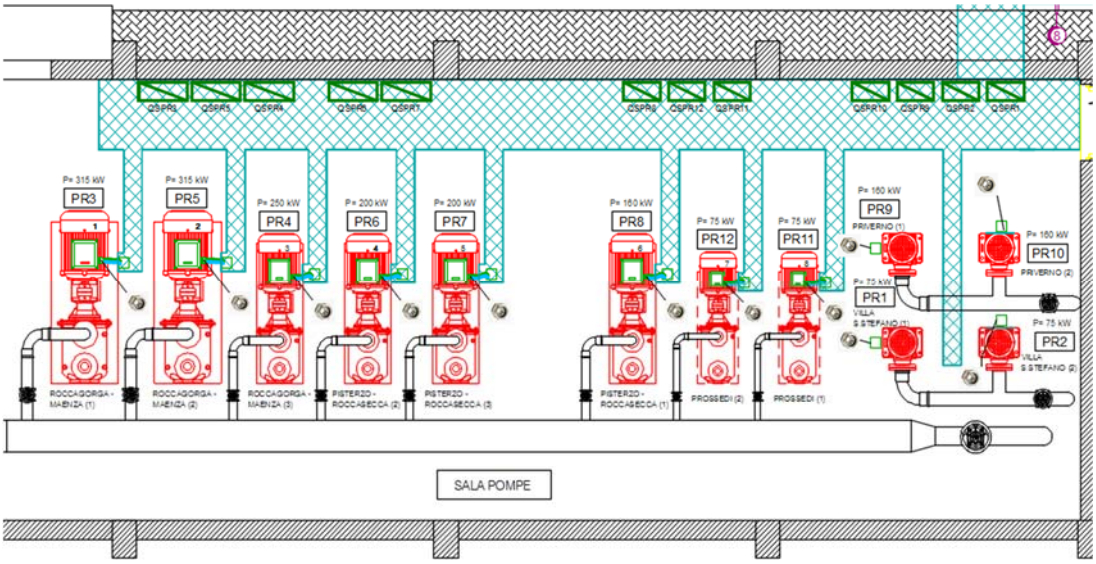

Fig. 2 –Water supply system layout

Data collected by the monitoring systems are: output pressure (bar), flowrate (m^3), energy demand (kWh), pump casing vibration (dB), rotational frequency (rpm). Data provided from the supply system manager ranging from 13th January to 9th February. Data sample frequency is 15 minutes and the size of dataset is 1386 samples. The pump considered in the study provide the water to Priverno district with magnitude 160 kW. Among these the measures employed in the analysis are flowrate (m^3) and vibration (dB).

4. Results

The neural network was trained on a time interval representative of stable pump operation. Then the trained network was used to predict the energy demand of the pump. Finally, the prediction, used as the pump energy base-line, was compared with real energy demand to provide an energy rating of the pump in a view to provide diagnostics.

Figure 3 shows the results of the train-and-predict network phases. The training and testing was performed in the range 13th January - 8th February and the prediction on energy demand extend to a day interval, i.e. 9th February. Data employed during the network training and testing are water flowrate, casing vibration and energy demand. Then during the network validation or prediction phase, the network input included only mechanical information such as flowrate and vibration level.

Figure 3(a) compares real energy demand to that predicted by network. Blue curve is the energy demand provided to train and test the network (original target), yellow and red curves respectively represent the expected output and the network prediction. Fig. 3(b) provides the percentage error of prediction, computed trough the difference between prediction and expectation. Red and blue curves represent the training and testing percentage error, both with the same order of magnitude.

The network testing results show the ability of the network to predict quite well one-day time interval with a maximum error of 0.16 % on energy demand.

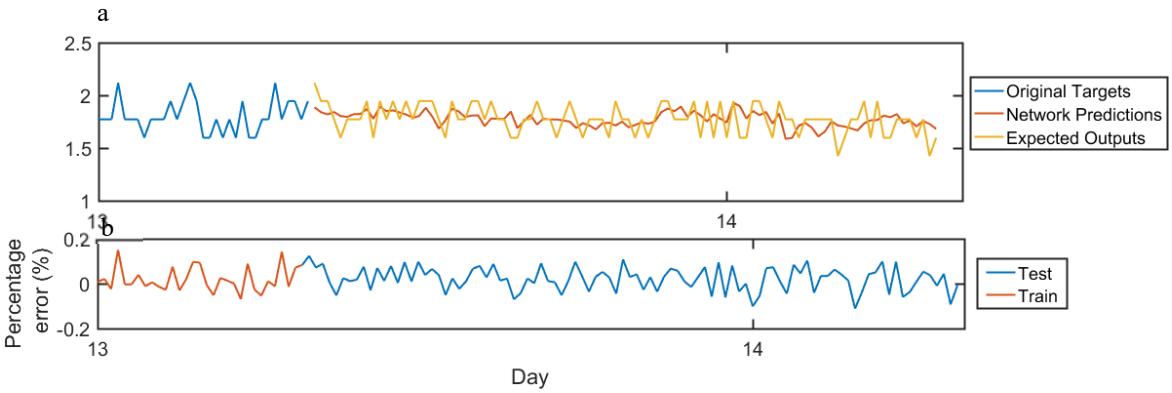

Fig. 3 – Network testing phase: (a) comparison between real energy demand and predicted by network; (b) percentage error of prediction.

The network training and testing was performed on a time interval related to a stable running of the pump ranging from 13th to 24th January. Then it was validated on 25th January – 9th February. Fig. 4 shows results related to pump energy modeling and rating. Fig. 4(a) compares the real energy demand to that predicted by the network. Blue curve is the energy demand provided to train and test the network (original target), yellow and red curves represent respectively the expected output and the network prediction. Here we observe deviations between prediction and expectation; these deviations are used to rating the energy behavior of the pump. Fig. 4(b) provides the percentage error of prediction, computed trough the difference between prediction and expectation. Red and blue curve represent the training and testing percentage error on energy demand. We observe that during training the percentage error is holding steady, instead during validation interval change on time increasing and decreasing. Employing the network prediction as energy model, deviations of real consumption from the model are seen as performance improvement or worsening; providing the energy rating of the system. More specifically, positive and negative values of percentage error represent respectively the worsening and the improvement of energy performance.

Fig. 5 compares the percentage error (Fig. 5 (a)) with the energy demand and flowrate normalized graphs (Fig. 5(b)). Both the percentage error and acquired data graphs were mediated, with the aim to mitigate the sharp fluctuation. Green dashed and dotted rectangle represent respectively high and low energy performance. Observing Fig. 5 we observe the improvement of energy performance when the normalized energy decreases compared to flowrate and vice-versa its worsening when normalized energy increases compared to flowrate. In conclusion, Figure (5) graphically confirms the ability of percentage error to provide an energy rating of the system.

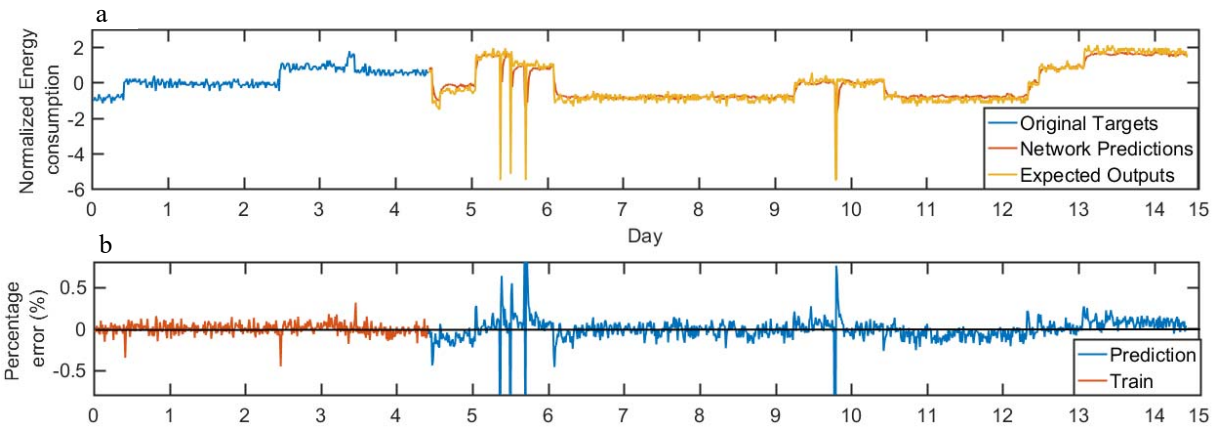

Fig. 4 – Network application phase: (a) Comparison between real energy demand predicted by network; (b) percentage error of prediction

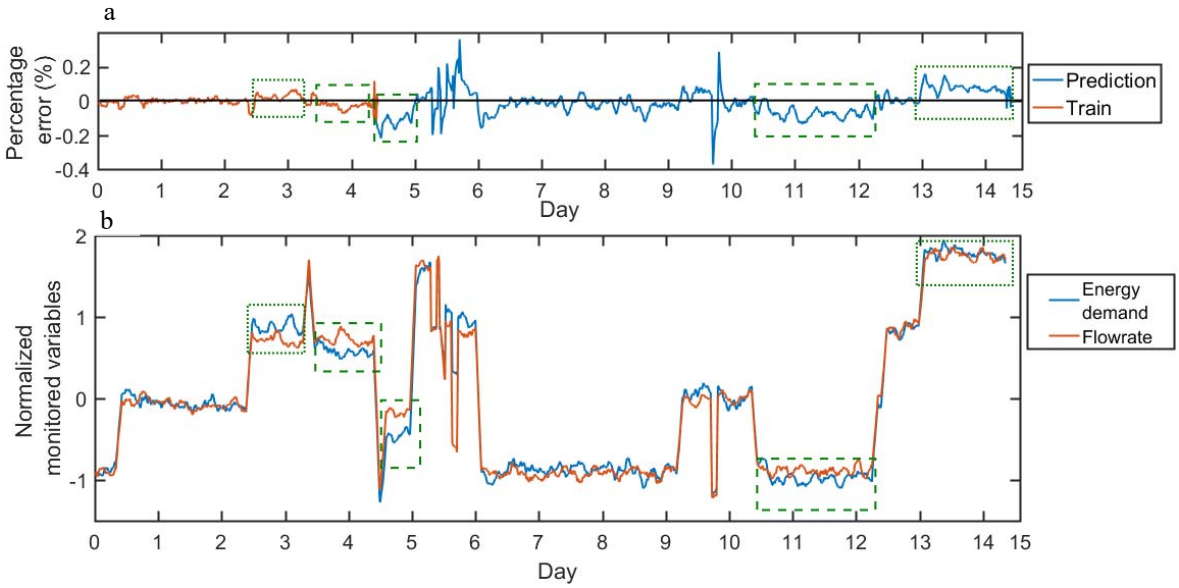

Fig. 5 - (a) percentage error; (b) energy demand and flowrate normalized graphs

The selection of predictor variables (flowrate, and vibration) was dictated by the need of the installations operator to get indications about energy performance from very little monitored variables. On the other hand, the selected quantities are related both to the process (flowrate) and to the pump working condition (vibration); and are usually monitored in water supply systems.

To demonstrate the right choice of variables, from the point of view of model construction and consequently for the evaluation of energy efficiency, the percentage error of network prediction was checked against another network prediction trained with pressure and flowrate (Fig. 6).

Percentage error in Fig. 6 (a) results very similar to percentage error in Fig. 6 (b), proving the validity of the model constructed on flowrate and vibration as training variables.

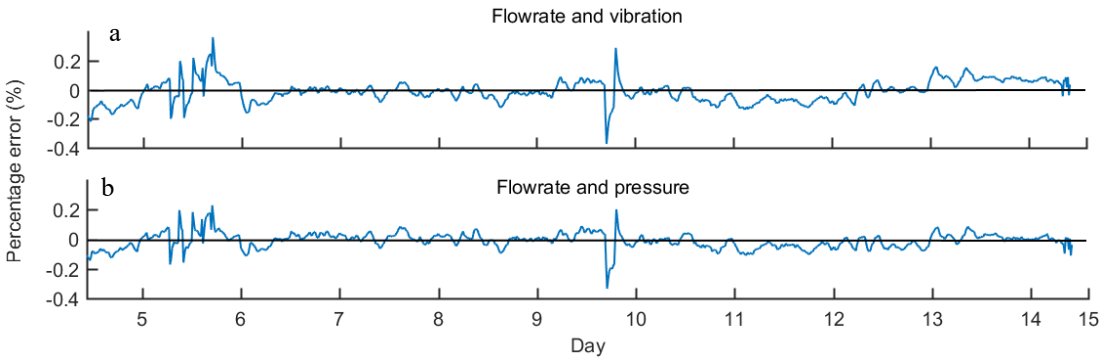

Fig. 6: (a) percentage error of network trained with flowrate and vibration;(b) percentage error of network trained with flowrate and pressure

5. Conclusion

The work aimed to define new metrics for the energy rating of a water supply system. The purpose is to define a methodology able to understand the dynamics within the system and to provide a metrics for the evaluation of the energy performance. On the other hand, the requirement to investigate the correlation among different monitored data, led to the selection of data intensive techniques. Specifically, among them the NARX neural network was employed

for its ability in the forecasting of dynamic system. The methodology was applied to the evaluation of energy efficiency of a pump that is part of a water supply system located in Latina (Italy).

In this work, NARX network was employed to provide a model of the energy use of the system.

At first the ability of the network prediction was tested on one day. The network testing results show the ability of the network to satisfying predict one-day time interval with a maximum error of 0.16 % on energy demand. The network was trained on a time interval related to a stable running of the pump. Employing the network prediction as energy model, deviations of real consumption from the model are seen as performance improvement or worsening; providing the energy rating of the system. This value was compared with the energy demand and flowrate normalized graphs which visually confirm the ability of percentage error to provide an energy rating of the system.

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