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IMPROVEMENTS IN WATER SUPPLY SYSTEMS BASED ON OPTIMIZATION AND RECOGNITION OF CONSUMPTION PATTERNS

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Abstract

Water supply systems consume large amounts of energy because of the pumping processes involved. The operational strategy of using frequency converters enables the system to work with better adjusted discharge rate to meet demand. In this case, an optimization strategy can establish an optimal procedure in order to schedule the rotational speed of pumps over a period and guarantee a volume of water in the supply tank. This work presents and solves an optimization problem that provides the optimal schedule for the rotational speed of pumps in a real water supply system considering minimizing the use of electricity and the cost thereof and maintenance. The optimization problem is based on two Artificial Neural Networks (ANN) models that provide the total power consumption in the pumping system and level of water in the tank. Pattern recognition techniques in univariate time series based on the real data are used to forecast the demand curve according to the season ofthe year. The results show the potential savings generated by the proposed method and show the feasibility of scheduling the rotational speed of the pumps to ensure the minimum energy cost without affecting hourly demand and the security of the supply system.

Keywords: Optimization, Energy efficiency, Water supply system, Pattern recognition.

1. Introduction

The growing demand for electricity has a direct impact on the environment,

Nomenclatures

c	Number of clusters
d	Demand of water, m³/h
F	Neural model
H	Piezometric head, m
$h(t)$	Water level at time t, m
$\hat{h}_k$	Water level at discrete time$k$, m
i	Index
k	Discrete time, h
n	Number of demand curves (objects)
$P(t)$	Power consumed at time, kW
Q	Flow, m³/h
rot_i	Rotational speed of pump i, rpm
t	Time, h
t_c	Time of work cycle, h
t_{tr}	Tariff rate, US$
u	Membership degree

Greek Symbols

η_b	Efficiency of the pump
γ	Specific weight of water, kN/m

especially considering that the global model of electric power generation is based mainly on fossil fuels [1]. Economic impacts are also felt from power cuts, poor power quality, high electricity prices and tariff increases in periods of high consumption. Industry is a large consumer of electricity and the pumping process of a water supply system too. Intervention to improve the energy efficiency of such systems provides economic and environmental benefits to the organization and society as a whole.

In general, a water supply system comprises a pumping station, storage tank and pipeline. It is a typical dynamic system where the flow and pressure profiles over the pipeline and water level in the tank vary according to the demand flow and the discharge flow controlled in the pumping station. In general, the volume of extra water in the storage tank within a work cycle constitutes a waste of energy because the pumped flow rate is higher than the water demand [2]. In this case, the operational policy seeks to maintain the water level unchanged throughout a work cycle (usually 24 hours).

In most cases, the procedure of flow control in the pumping station comprises traditional methods of pumping using an on/off switch. In other words, the operational policy establishes the number of pumps in operation at each hour to replenish the volume of water in the tank (in each work cycle) to meet the daily demand [3, 4]. Fixed speed pumping is widely used in water supply systems. On the other hand, the use of frequency converters (variable speed pumping) can minimize power consumption more efficiently, enabling the discharge rate to be better adjusted to meet daily demand without excess water in the tank or excessive power consumption [5-8].

Some works present optimization strategies for water supply systems with other objectives not just to cut the cost of energy. Lansey and Awumah [9], Lopez-Ibanez et al. [10] and Vladimir et al. [11] consider the maintenance costs associated with pumps. These costs are directly related to the number of changes in the state (on/off). If the pump is kept running for a long time this minimizes maintenance costs [9]. Wang and Guo [12] also consider the problem of siltation of a water well in a multi-objective function. Jowitt and Germanopoulos [4] and McCormick and Powell [13] include a soft constraint in order to minimize the event of exceeding the maximum energy demand. Georgescu et al. [14] consider a soft constraint to minimize the difference between the initial and final level of the storage tank during a work cycle.

Optimization problems in water supply system can be solved by classical optimization methods such as linear and nonlinear programming [4, 15-16] and dynamic programming [13, 17-18]. Some works use methods based on combinatorial optimization [11, 14, 19-20]. In larger water supply systems the use of conventional or traditional methods for solving optimization problems, based on the phenomenological models, implies high computational effort.

Alternatively, most recently optimization models use artificial intelligence techniques based on Artificial Neural Network (ANN) as a replacement for traditional methods of optimization. Rao et al. [21] present an optimal control problem applied to supply system and water distribution networks. A dynamic model based on ANN was developed to predict the combination of pumps and valves to meet the demand considering a work cycle of 24 hours. This model is used in an optimization algorithm that considers operating costs of pumping together with hydraulic constraints.

The demand curve is an input in the modelling of water supply systems and a disturbance in optimal control problems. The demand curve effects the operation of the pumps directly, the energy consumption and it can also be used to support decision-making in procedures of pumping operation [22]. In general, the daily demand for water is predicted in a heuristic and intuitive way based on the knowledge and experience of operators in water supply systems [23-25]. On the other hand, the prediction of the demand curve depends on seasonal aspects associated to the climate records of the region throughout the year.

This work presents and solves a dynamic optimization problem to provide an optimal schedule for the rotational speed of pumps in a water supply system so as to minimize electricity and maintenance costs. The case studied comprised a real case of a segment of the water supply and distribution system in Salvador (Brazil). The pumping procedure considers the use of frequency converters and the dynamic behaviour of the system is represented by two MISO (Multiple Input Single Output) ANN's capable of predicting the level of the storage tank and power consumption at any time. Patterns of demand curves are recognized based on the real data using the Fuzzy-C-Means (FCM) method, a well-known method belonging to the C-Means families of batch clustering models [26, 27], suitable for clustering objects represented by time series [28].

2. The Case Study and Optimization Problem

The pumping station selected, called PS High Load, works continuously and is composed of four identical centrifugal pumps (Fig. 1) operating in parallel. The PS High Load has a maximum capacity of 8800 m^3/h (all the pumps operate at nominal rotational speed of 1175 rpm). The PS High Load pumps are arranged in parallel. In addition, the flow of water in the suction inlet of the pump occurs by gravity.

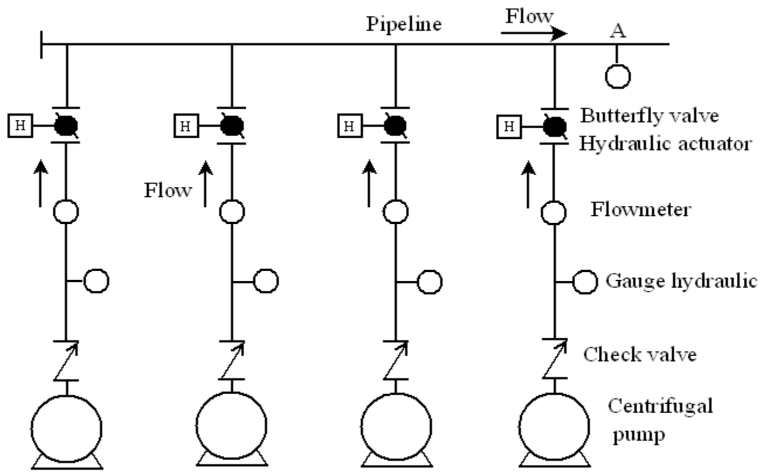


Fig. 1. Simplified Hydraulic Scheme of the PS High Load.

All treated water is pumped and flows along a large diameter pipe (main line, 1.5 m in diameter and pipe wall thickness of 0.04 m) to the reservoir (storage tank). The water main line is made of carbon steel and has a total length of 5600 m. The quota profile of the water pipeline is shown in Fig. 2. In practice, lower energy costs are achieved by reducing pumping during periods when electricity rates (tariffs) are higher.

In addition, a reduction in the maintenance costs is based on the approach described by Lansey and Awumah [9] limiting the change in the pump status (on/off) to just once at the beginning of each hour in the work cycle (24 hours).

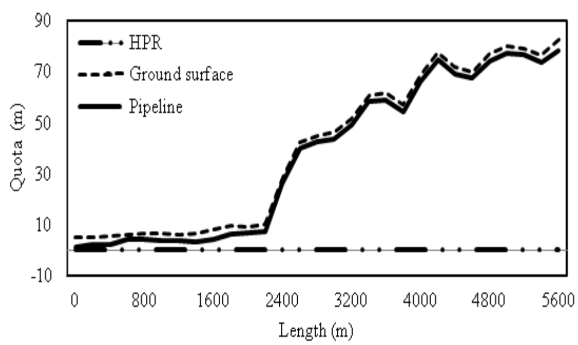


Fig. 2. The Quota Profile - Water Main Pipeline (HPR - Horizontal Plane of Reference).

Diniz et al. [29] present a complete phenomenological model of distributed parameters for the PS High Load as shown in Figs. 1 and 2, capable of predicting the hydraulic behaviour and the energy consumption. This model comprises design parameters and properties of the real system. The simulation results show piezometric head and flow profiles consistent with the reality and the comparison with real data (volumetric flow rate at the beginning of the main line and water level in the tanks) shows that the model describes the dominant dynamic of the system well.

The simulation also considers the use of frequency converters in pumps in order to vary the rotational speed of pump between maximum and minimum limits of operation. The numerical approach to simulate this system is based on the phenomenological model (one-dimensional time-dependent partial differential equations) which comprises the use of the line method [30-32]. The spatial domain of the problem (main-line) was divided into segments of same length. Considering the higher dimensions of the case studied, this numerical strategy results in a system of 224 differential equations.

The optimization model proposed in order to provide the optimal operational schedule for the pumping station (variable speed) is similar to that developed by Brion et al. [17]. The power consumed at time t is a function of the flow and piezometric head in the discharge of the pumping station ($Q(0,t)$ and $H(0,t)$) and also of the global efficiency of the pumping station ($\eta_b(t)$).

$$P\left(t\right) = \gamma \cdot \frac{Q\left(0,t\right) \cdot H\left(0,t\right)}{\eta_b\left(t\right)} \tag{1}$$

At any time, the global efficiency is the product of the efficiency of all pumps in operation. Equation (1) establishes that the power consumed is directly related to the dynamic profiles of flow and pressure over the pipeline.

The optimization model comprises the following objective function:

$$minimize \;\; FO\left(rot_i\,(t),\; i = 1,\ldots,4\right) = \int_0^{t_C} P(t) \cdot t_{tr}\,(t) \cdot dt \tag{2}$$

Subject to the following constraints:

a) Limits on the rotational speed to avoid problems of over-pressure or cavitation:
   For the pump number 1:
   $1120 \text{ rpm} \leq rot_1(\text{t}) \leq 1175 \text{ rpm}$
   This pump is always working in order to avoida break in supply.
   For the other three pumps (i=2, 3, 4):
   $0 \leq \text{rot}_\text{i}(\text{t}) \leq 1175 \text{ rpm}$
   whereas $rot_i(t) = 0$ if $rot_i(\text{t}) < 1120\, rpm$

b) Limits on the water level inside the storage tank
   $3.0 \text{ m} \leq h(t) \leq 15.5 \text{ m}$

The objective function is the total cost of power consumption (kWh) in a work cycle (t_c) (24 hours). The t_{tr} is the tariff rate established for the time instant t. $rot_i(t)$ (i=1,…,4) is the solution to the problem (optimal schedule for the rotational speed in each pump).

This optimization problem comprises two outputs of the PS High Load, namely, the power consumed $P(t)$ and the water level in the storage tank $h(t)$.

The former is a function of the state variables (flow and piezometric head along the pipeline) and the second is a state variable of this model related to the mass balance in the storage tank [29]. Considering that the size of the phenomenological model makes it inappropriate for the optimization purposes, a strategy of model reduction is adopted using empirical models based on Neural Networks (NN). Therefore two additional equality constraints must be included in the optimization model in order to consider the model of the PS High Load.

$$h(t) = f_1\left(rot_1(t), rot_2(t), rot_3(t), rot_4(t), d(t)\right) \quad (3)$$

$$P(t) = f_2\left(rot_1(t), rot_2(t), rot_3(t), rot_4(t), d(t)\right) \quad (4)$$

where f_1 and f_2 represent the respective neural models and d is the demand (input). The use of NN of optimization has advantages over traditional modeling approaches. This model structure enables efficient handling of large amounts of data with high generalization capability [33-35].

The NN model associated to the water level in the storage tank comprises a typical NARX (Non-linear AutoRegressive with eXogeneus inputs) structure which was identified (network training) feeding back the output predicted at a previous time (recurrent topology).

$$\hat{h}_k = f_3\left(rot_{1,k-1}, rot_{2,k-1}, rot_{3,k-1}, rot_{4,k-1}, d_{k-1}, \hat{h}_{k-1}\right) \quad (5)$$

where $\hat{h}_k$ is the water level predicted by the NN model at discrete time k.

Based on the operational features of the case studied (disturbances caused by the maneuvers in the pump operation based on the measurement of the hourly demand throughout the day), a sampling period of one hour is considered in the model identification and also in the optimization problem.

Unlike the NN model for the water level, the smaller time constant associated to the power consumed suggests a quasi-stationary approach and the NN model comprises a typical feedforward topology.

$$\hat{P}_k = f_4\left(rot_{1,k}, rot_{2,k}, rot_{3,k}, rot_{4,k}, d_k\right) \quad (6)$$

Both NN models comprise only one hidden layer (neurons with sigmoidal activation functions) and one output layer with one neuron (linear transfer activation function) so that these are equivalent to MISO (Multiple Input Single Output) model structures. All data were obtained through simulation of the phenomenological model. A cross validation procedure (Magalhães et al. [36] and Santos et al. [37]) was adopted using samples of training and test data (each one with 714 points).

The best results were obtained with eight and four neurons in the hidden layer for the NN models associated to the power consumed and water level in the storage tank, respectively. The comparison between the NN predictions and model data as shown in Figs. 3 and 4) shows the suitability of the use of NN models directly in the optimization problem.

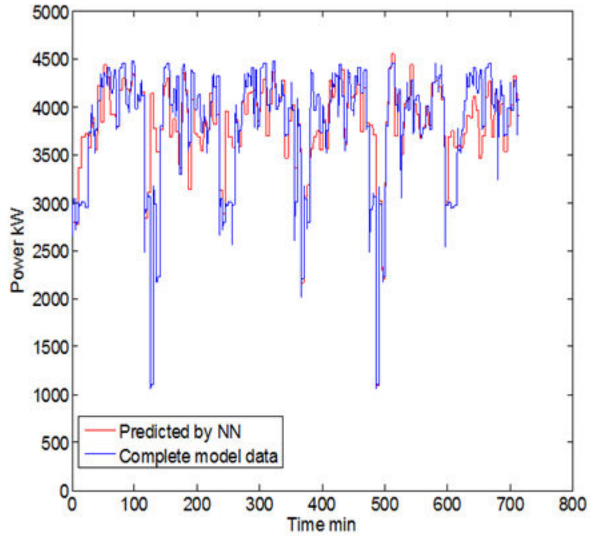


Fig. 3. Results of Validation Test to the Power Consumed.

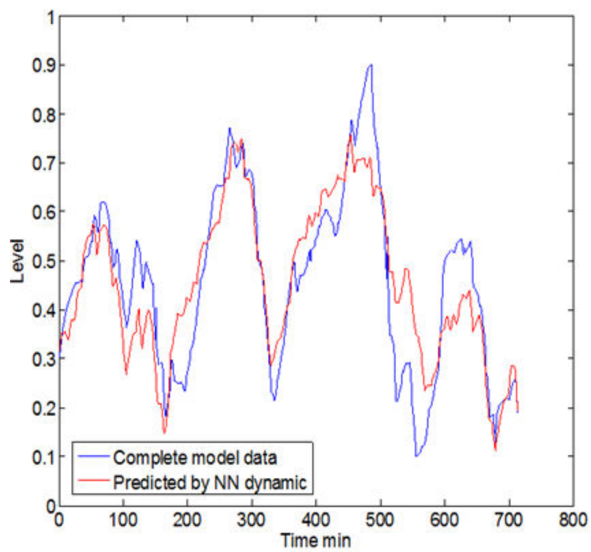


Fig. 4. Predicted Values by Recurrent NN Model and Measured Values.

3. Pattern Recognition - Demand Profiles

Multivariate analysis is a powerful tool for knowledge extraction especially when applying pattern recognition techniques based on data [38]. Data Mining methods (DM) that can extract useful information from data can be used to develop decision-making tools so as to improve production systems and management technology [36, 39-40].

The pattern recognition of demand curves enables prediction and decision-making in operational maneuvers in pumping stations toprovide greater reliability and efficiency for the supply system. Pattern recognition may also be useful for the prediction of chemicals for water treatment, for the planning of the network infrastructure and to support the operation of the pumping station. Furthermore, it can be used for long-term planning and design of infrastructure for a water supply system, and short-term (hours or days) use for the definition of operational procedures of pumping [41, 42].

In this work pattern recognition in demand profiles is treated as clustering of univariate time series (daily demand of water consumption) [28] according to the season of the year. There are few works based on pattern recognition applied to predict consumption profiles in water supply systems. Greenaway et al. [23] apply a pattern recognition technique based on univariate time series to predict demand profiles (shortand long-term) for a supply and distribution water company in a region with about 900,000 people. Based on the model applied to a short-term (24 h) scenario an optimization approach was developed for energy consumption. It reduced pumping at hours of high rates and also minimized the volume of water in the tank within a work cycle. The model was also used in a long-term scenario to support planning and financial management. Shvartser et al. [43] developed models of hourly demand curves based on the combination of two methods, namely, pattern recognition and time series analysis using the Markov process. The daily demand curve, considered a stochastic process, is modeled by the Markov chain process based on three segments (states) (patterns of increasing, decreasing and oscillating).

The initial sample comprised daily demand curves for the case studied (PS High Load) throughout 2010. A total of 335 daily consumption profiles were available. Clustering and pattern recognition was performed using the Fuzzy C-Means (FCM), a well-known method belonging to the C-Means families of batch clustering models [26, 27], suitable for clustering objects (in this case demand curves) represented by time series [28].

Based on the climatic features of the case study, the annual sample of daily demand profiles was arranged into three seasons, namely,spring (85 curves), autumn-winter (183 curves) and summer (67 curves). Autumn and winter were put together because of the historical similarity between these two seasons. Furthermore, this clustering (selection of seasons) was based on the average daily water demand associated to each of these seasons according to Table 1.

Table 1. Initial Clusters - Water Demand.

Seasons	Average daily (m^3/h)	Period
Spring	7843	September 23th to December 21th
Autumn-winter	7485	March 20st to September 22th
Summer	6933	December 22th to March 20th

Weekends and holidays are not considered in this analysis (this does not mean that a pattern for non-working days cannot be recognized). Initially, the set of demand curves associated with each season as shown in Table 1 was divided into validation and work samples, both randomly generated. The best results (using

FCM method) were obtained considering two clusters (and two patterns) for each season. Figure 5 presents the demand patterns (center of each cluster) recognized.

The similarity between the patterns recognized in the work and validation samples in the same season shows the consistency of the results. Furthermore, for each season the two consumption patterns present similar dynamic behavior throughout the day.

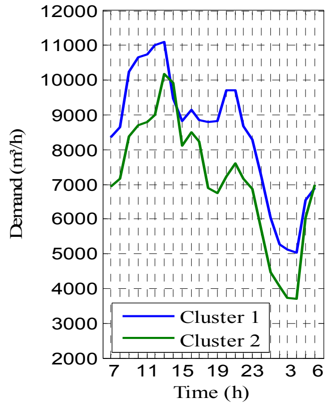
As expected for tropical regions, as in our case, the climatic differences among the seasons of the year are not very sharp and the total thermal amplitude observed is lower than for other regions with more well-defined seasons. In the region considered, the occurrence of milder temperatures is closely associated with higher rainfall. Based on the patterns recognized as shown in Fig. 5, the maximum average daily demand of water in the spring, autumn-winter and summer is equal to 7792 m³/h, 7342 m³/h, 5452 m³/h, respectively. The greatest demand for water in the spring (7 am and 1 pm) (Figs. 5(a) and (b)) is associated to the low rainfall levels in this period, compared with the autumn-winter season. On the other hand, in the summer the temperatures are the highest and sporadic rains occur. Despite this, the demand for water is quite low compared to that in spring and autumn-winter. This is because in summer many people are on vacation and leave the city which reduces demand significantly. Furthermore, schools are closed, therefore a specific operational policy for supply in this period is justified.

Another analysis comprises the evaluation of demand curves belonging to each cluster. The FCM method is a typical soft partition unlike other hard clustering methods based on crisp models such as the K-means algorithm [27, 44]. Considering n demand curves (objects), c clusters and the probabilistic approach, the partition matrix obtained by the FCM method contains the membership degree of each object $\left(u_{ki} \in [0,1],\ i = 1,\ldots,n \ \ k = 1,\ldots,c \ \text{ and } \sum_{k=1}^{c} u_{ki} = 1 \ \ \forall i\right)$ to each of the clusters recognized. Figure 6 presents the membership degree of each demand curve (spring and summer) to cluster 1. The set of membership degrees shows a good level of polarization in both cases (few values in the range [0.4, 0.6]) which also highlights the good quality of the clustering.

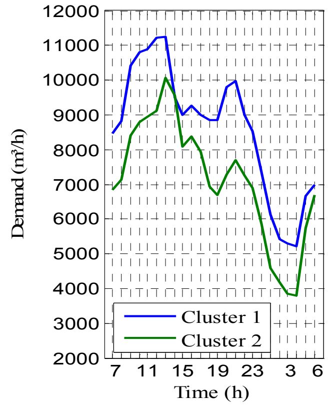
Table 2 presents the number of objects belonging to each cluster (both samples - work and validation) based on the membership degrees associated to each object.

According to Table 2 the number of objects belonging to each cluster are quite similar (mainly in spring and summer) which does not justify the choice of a modal cluster (cluster with the highest number of demand curves) [38] to represent each season. Figure 7 presents the mean demand profiles of each season.

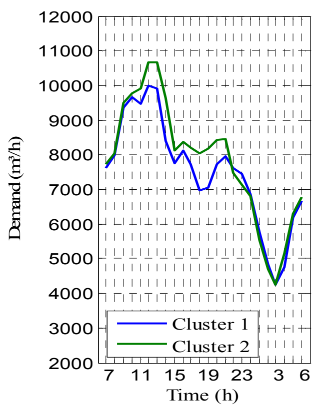
Despite the similar dynamic behavior of daily consumption among the three patterns presented in Fig. 7, which is also a consequence of the climatic features of the region under study, quantitative differences in demandmay require different policies or operating procedures of pumping. According to Fig. 7, the demand profile for spring is the highest in the whole cycle. The small difference among the average temperatures in the seasons (low thermal amplitude throughout the year) contributes to the uniformity of consumption. Even in autumn-winter water consumption is high in the early morning (5 to 8 am).



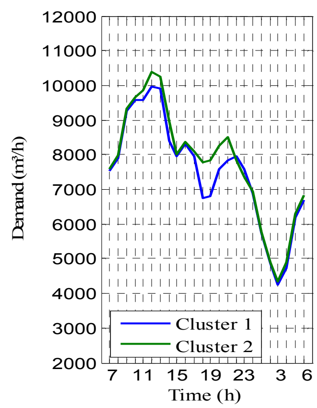
(a) Spring– Work Sample.



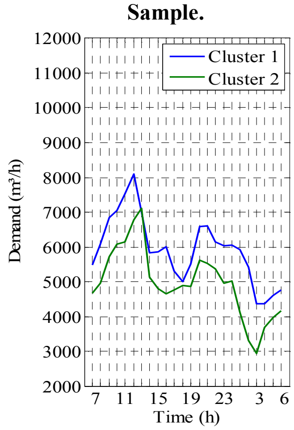
(b) Spring– Validation Sample.



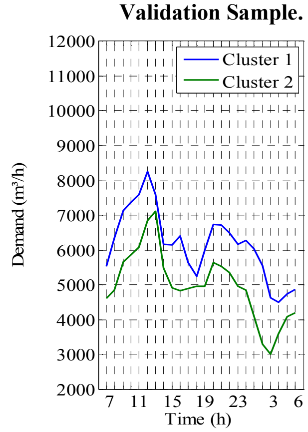
(c) Autumn-Winter-Work Sample.



(d) Autumn-Winter– Validation Sample.

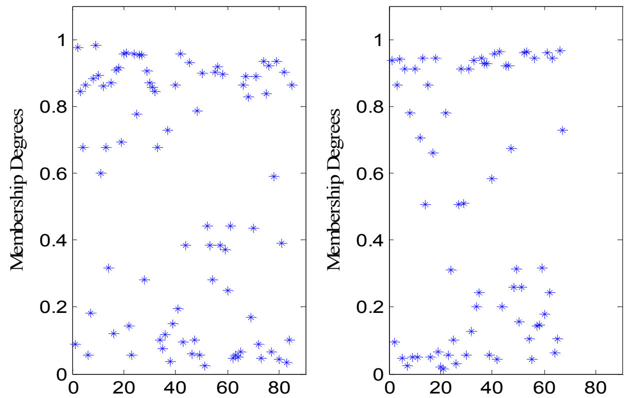


(e) Summer – Work Sample.



(f) Summer – Validation Sample.

Fig. 5. Patterns of Daily Demand by Season.



(a) Spring. (b) Summer.

Fig. 6. Membership Degree – Cluster 1.

Table 2. Number of Objects (Demand Curves) in Each Cluster.

Seasons	Cluster 1		Cluster 2	
	Objects	Curves (%)	Objects	Curves (%)
Spring	45	52.9	40	47.1
Autumn-winter	83	45.4	100	54.6
Summer	34	50.7	33	49.3

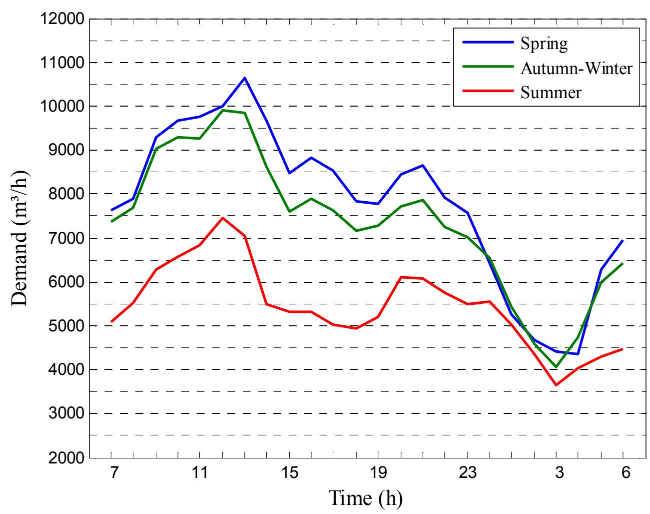


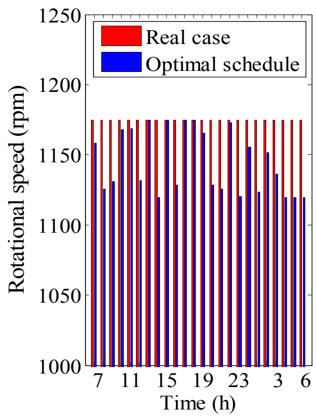
Fig. 7. Demand Profiles.

The greatest demand for electricity in the entire electrical system of the region considered occurs in the period from 5 pm to 8 pm. The electricity tariffs in this period increase in order to avoid overloading. According to Fig. 7 the highest water demand in this period occurs in the spring. The efficient management, planning and control of supply in these peak hours especially in this season can lead to a reduction in the operational costs of pumping.

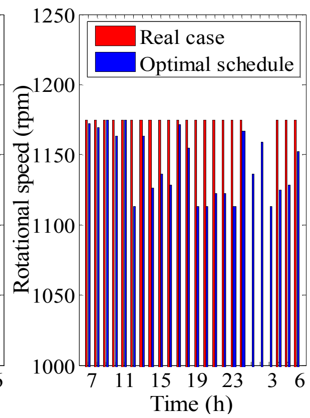
4. Results and Discussions

4.1. Optimization tests

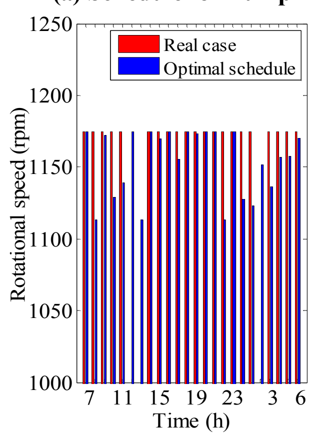
The first optimization tests compare results obtained with variable speed pumping (optimal schedule using frequency converters) and real data from the system studied (fixed speed pumping), considering a typical demand curve for both cases. Figure 8 presents the optimal schedule for the rotational speed of pumps together with the schedule used in the real case (fixed speed pumping) according to the operational policy. Figure 8 (a) shows that pump 1 works continuously for 24 hours. This avoids the interruption of the water supply. Unlike the standard procedure (fixed speed pumping), the speed rotation of pump 1 may be reduced according to the constraints considered (Eq. (2)). In optimal scheduling the rotational speed of pumps are reduced in the peak period of electricity consumption. All pumps operate at below maximum speeds for at least one hour during the peak period. Apart from the economic impact of the optimal schedule, it also improves the safety of the electrical system reducing the need for investment to expand power generation.



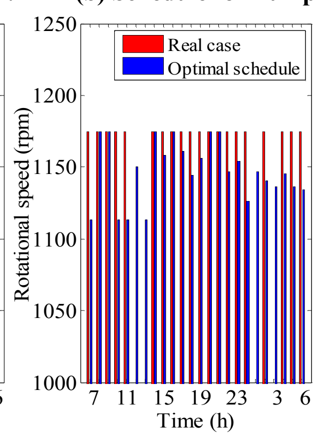
(a) Schedule for Pump 1.



(b) Schedule for Pump 2.



(c) Schedule for Pump 3.

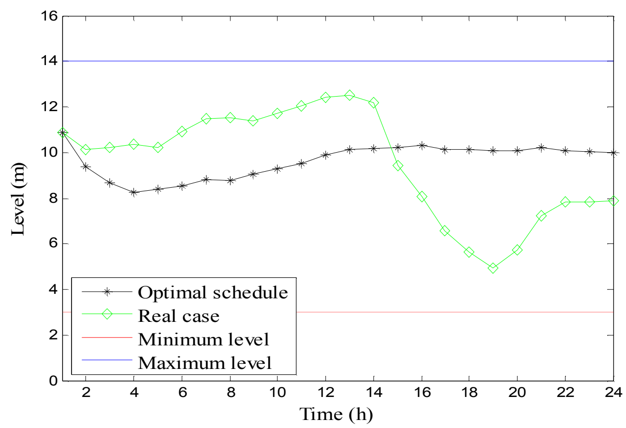


(d) Schedule for Pump 4.

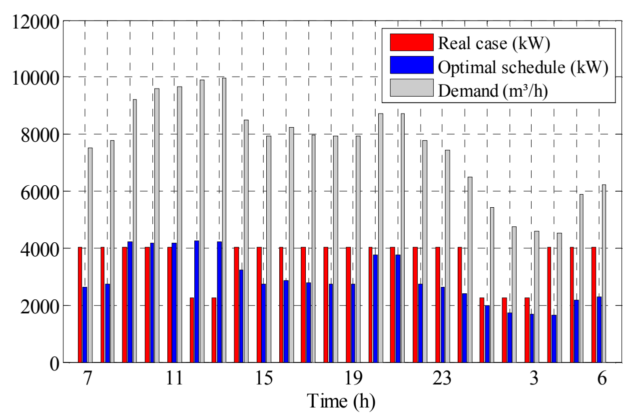
Fig. 8. Pumping Schedule.

Figure 9 presents the water level in the storage tank and the power consumed by the pumping station. The water level profile in the case of optimal schedule suggests that there is no excess in the flow discharge of the pumping station during the work cycle. The initial and final levels are very close unlike in reality. Large differences between initial and final levels can lead to water shortage causing a need for daily monitoring.

The reduction in the power consumed in the real case as shown in Fig. 9(b) (12 am, 1 pm and 1 am to 3 am) is associated with the shutdown of pumps. The schedule of the real case does not seek to minimize the cost of energy in the period of greatest demand for electricity in the entire electrical system (5 pm to 8 pm), the period when electricity is the most expensive. All pumps were in operation during this period before. Furthermore, the four pumps operated simultaneously with the maximum speed for a long period (73% of the work cycle). The profile of power consumption associated to the optimal schedulehas a dynamic behavior similar to the demand curve. From 5 pm to 8 pm (consumption peak) the optimal schedule results in a reduction in electricity consumption.



(a)



(b)

Fig. 9. (a) Water Level in the Tank - (b) Power Consumption and Water Demand.

Figure 10 presents the electricity saved resulting from the use of frequency converters and the optimal pumping scheduling. According to Fig. 10, considering an efficiency of frequency converters equal to 97% of the total power consumed by the pumps [45], the results show a power saving approximately equal to 17.1%. Based on an average tariff of US$ 0.108/kWh [46] and an average monthly consumption of electricity of 2,646,000 kW (or 88,200 kW/day). The estimated monthly cost of electricity is US$ 285,768.00. The average monthly amount of energy saved is equal to US$ 48,980.64. Considering the initial investment of US$ 284,000.00 for the purchase, building and installation of frequency converters, the estimated payback time is 6 months.

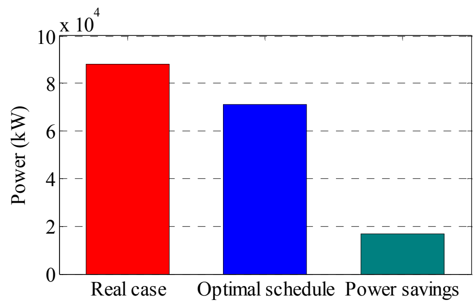


Fig. 10. Power Saving.

The differences in demand values between the patterns of the same season as shown in Fig. 5 would suggest the need for different operational schedules. Figure 11 presents the optimization results considering the two demand patterns of spring (season with the highest Euclidean distance between the patterns, Figs. 5 (a) and (b).

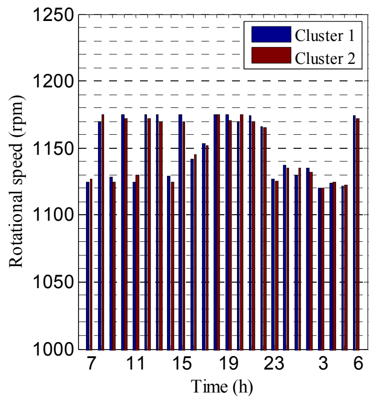
Figure 11 shows that the optimal schedule of pumps are similar in most of the work cycle. With few exceptions, the pumps are switched (on/off) in the same instants. Also, for each pump there are small differences between the rotational speed. Therefore, for the purposes of determining the optimal pumping schedule associated to each season, any of the patterns could be considered or a mean demand profile such as in Fig. 7 can also be used as input for the optimization problem. This reasoning can be applied for the other seasons (autumn-winter and summer) with greater similarity between the patterns.

Figure 12 compares the optimization results for the three seasons considered, based on the pattern of higher average demand for each one.

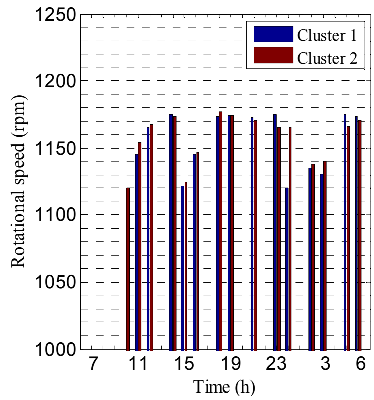
The differences between the pumping schedule of each season suggests a change in operational policy for the PS High Load. Table 3 presents the daily power consumed in each season. The difference between spring and summer (higher and lower average daily water demand respectively) (20,322 kW) confirms that the same demand profile should not be considered throughout the year.

Table 3. Power Consumed by Pumps.

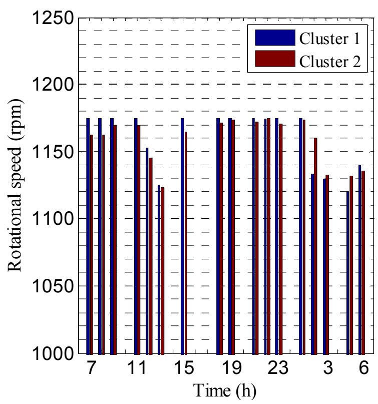
Seasons	Power kW
Spring	92,282
Autumn-winter	83,137
Summer	71,960



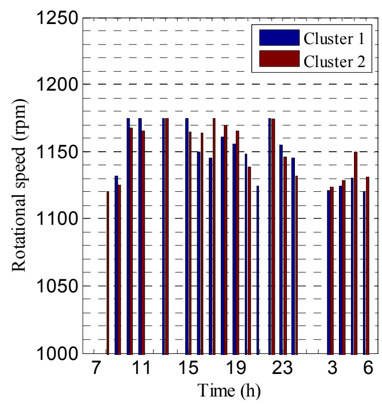
(a) **Pump 1.**



(b) Pump 2.

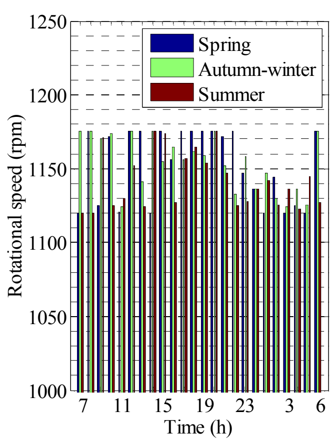


(c) Pump 3.

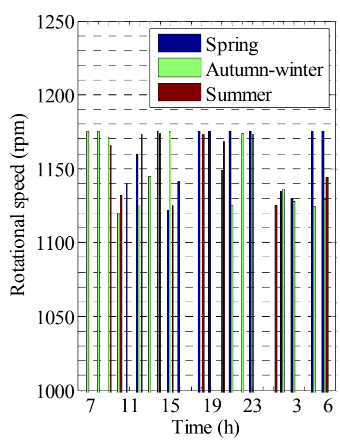


(d) Pump 4.

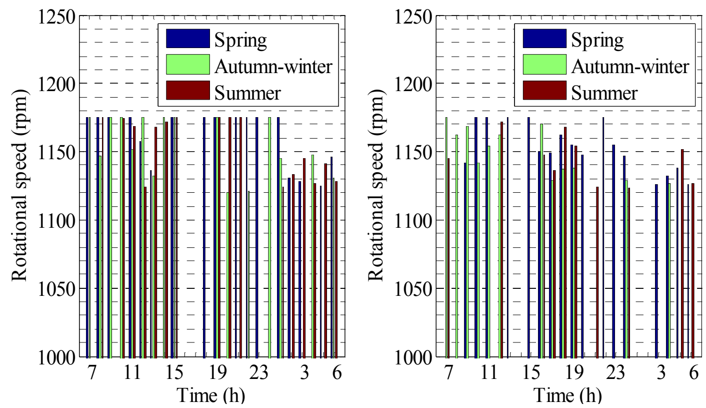
Fig. 11. Pumping Schedule - Spring Season.



(a) Pump 1.



(b) Pump 2.



(c) Pump 3. (d) Pump 4.

Fig. 12. Pumping Schedule for Each Season.

4.2. Advantages and disadvantages

Beyond the satisfactory results obtained, the proposal for dynamic optimization of a water supply system integrated into a strategy of pattern recognition in consumption profiles presents some advantages:

- Effectiveness and feasibility. Besides the need for frequency inverters, the implementation of the method does not require the installation or acquisition of complex systems. Pattern recognition can be updated periodically from data consumption curves;
- Change in the operating culture of the supply unit. The previous operating procedures, based on a heuristic approach, would be replaced by a new approach which is justified by the gain in energy efficiency together with the rational meeting of demand;
- Applicability. Despite having been applied and tested in an urban unit supply, the procedure and approach adopted can be applied to other water supply systems where specific hydraulic supply or operational features can be considered as additional constraints in the optimization problem;
- Model reduction approach. The reduction model strategy using two empirical models based on neural networks (NN) is important in enabling the implementation of real-time optimization.

Other aspects (or disadvantages) must be highlighted:

- Increased operating costs. Although the payback time associated with the purchase, building and installation of frequency converters is only 6 months, the cost of maintenance, improvement of data acquisition systems and training must be considered;
- Modeling and simulation. The impact of any change in the optimization problem or in the consumption patterns should be evaluated through simulation. In this case, empirical models must be identified or updated in offline mode using a phenomenological model or real data.

5. Conclusions

This work presents and solves a dynamic optimization problem that provides an optimal schedule for the rotational speed of pumps in a water supply system designed to reduce the amount spent on electricity and maintenance. The optimization strategy considers the use of frequency converters to meet the water demand without excessive accumulation of water in the storage tank within a work cycle. Patterns of demand curves were recognized based on real data using a well-known method suitable for pattern recognition in univariate time series.

Considering a typical demand curve and additional aspects associated to the efficiency, purchase and installation costs of frequency converters, the optimization results present savings in average monthly consumption of energy equal to US$ 48,980.64 for the case studied (PS High Load with maximum capacity of 8,800 m^3/h, main line with 1.5 m in diameter and total length of 5,600 m). These results demonstrate the improvement in energy efficiency of the water supply system through the use of an optimal control strategy. A 17.1% reduction (daily consumption) in the power consumed is achieved in the pumping system.

Pattern recognition applied to demand in a water supply system over a year is a useful way to optimize the pumping schedule and support planning and decision-making at operational level. The difference between the daily amount of electricity consumed in each season, according to the optimal pumping schedule, demonstrates that the same demand profile should not be considered throughout the year.

Lastly, the results and the method presented demonstrate the improvements in energy efficiency in the water supply system, the feasibility of predicting consumption patterns in a non-heuristic way and the use of these patterns directly in the optimization problem.

References

1. IEA-International Energy agency. (2011). *World Energy Outlook*. Paris: WEO.
2. Ormsbee, L.E.; Walski, T.M.; and Sharp, W.W. (1989). Methodology for improving pump operation efficiency. *Journal of Water Resources Planning and Management*, 115(2), 148-164.
3. Zessler, U.; and Shamir, U. (1989). Optimal operation of water distribution systems. *Journal of Water Resources Planning and Management*, 115(6), 735-752.
4. Jowitt, P.W.; and Germanopoulos, G. (1992). Optimal pump scheduling in water-supply networks. *Journal of Water Resources Planning and Management*, 118(4), 406-422.
5. Lingireddy, S.; and Wood, D.J. (1998). Improved operation of water distribution systems using variable-speed pumps. *Journal of Energy Engineering*, ASCE, 124(3), 90-103.
6. Collins, S. (1991). Variable-speed drive boosts pump efficiency. *Power*, 135, 164-165.
7. Lambeth, J.; and Houston, J. (1991). Adjustable frequency drives saves energy. *Water Environment and Technology*, 3(5), 34-45.

8. Bortoni, E.A.; Almeida, R.A.; and Viana, A.N.C. (2008). Optimization of parallel variable-speed-driven centrifugal pumps operation. *Energy Efficiency Journal*, 1(3), 167-173.
9. Lansey, K.E.; and Awumah, K. (1994). Optimal pump operations considering pump switches. *Journal of Water Resources Planning and Management*, 120(1), 17-35.
10. López-Ibáñez, M.; Prasad, T.D.; and Paechter, B. (2008). Ant colony optimization for optimal control of pumps in water distribution networks. *Journal of Water Resources Planning and Management*, 134(4), 337-346.
11. Vladimir, Ć.; Heiliö, M.; Krejić, N.; and Nedeljkovc, M. (2010). Mathematical model for efficient water flow management. *Nonlinear Analysis: Real World Applications*, 11(3), 1600-1612.
12. Wang, H.; and Guo, W. (2010). ACO optimizing neural network for macroscopic water distribution system modeling. *Proceedings of International Conference on Intelligent Computing and Cognitive Informatics*, Washington, United States, 367-370.
13. McCormick, G.; and Powell, R.S. (2013). Optimal pump scheduling in water supply systems with maximum demand charges. *Journal of Water Resources Planning and Management*, 129(5), 372-379.
14. Georgescu, S.; Popa, R.; and Georgescu, A. (2010). Pumping stations scheduling for a water supply system with multiple tanks. University "Politehnica" of *Bucharest Scientific Bulletin, Series D: Mechanical Engineering*, 72(3), 129-140.
15. Chase, D.V.; and Ormsbee, L.E. (1989). Optimal pump operation of water distribution system with multiple storage tanks. *Proceedings Conference on Water Resources Planning and Management*, Sacramento, United Sates, 733-736.
16. Yu, G.; Powell, R.S.; and Sterling, M.J.H. (1994). Optimized pump scheduling in water distribution systems. *Journal of Optimization Theory and Application*, 83(3), 463-488.
17. Brion, L.M.; and Mays, L.W. (1991). Methodology for optimal operation of pumping stations in water distribution systems. *Journal of Hydraulic Engineering*, 117(11), 1551-1569.
18. Nitivattananon, V.; Sadowski, E.C.; and Quimpo, R.G. (1996). Optimizaton of water supply system operation. *Journal of Water Resources Planning and Management*, 122(5), 374-384.
19. Tarquin, A.J.; and Dowdy, J. (1989). Optimal pump operation in water distribution. *Journal of Hydraulic Engineering*, 115(2), 496-501.
20. Barán, B.; Lücken, C.V.; and Sotelo, A. (2005). Multi-objective pump scheduling optimization using evolutionary strategies. *Journal of Advances in Engineering Software*, 36(1), 39-47.
21. Rao, Z.F.; Wicks, J.; and West, S. (2007). Optimising water supply and distribution operations. *Proceedings of the Institution of Civil Engineers - Water Management*, 160(2), 95-101.
22. Ghiassi, M.; Zimbra, D.K.; and Saidane, H. (2008). Urban water demand forecasting with a dynamic artificial neural network model. *Journal of Water Resources Planning and Management*, 134(2), 138-146.

23. Greenaway, G.; Guanlao, R.; Bayda, N.; and Zhang, Q. (2008). Water distribution systems demand forecasting with pattern recognition. *Water Distribution Systems Analysis Symposium*, Cincinnati, United States, 1-16.
24. Walski, T.M.; Chase, D.V.; Savic, D.A.; Grayman, W.; Beckwith, S.; and Koelle, E. (2003). *Advanced water distribution modeling and management*. Waterbury: Haestad Methods Inc.
25. Mays, L.W. (2000). *Water distribution systems handbook*. New York: McGraw-Hill.
26. Bensaid, A.; Lawrence, O.H.; Bezdek, J.C.; and Clarke, L.P. (1996). Partially supervised clustering for image segmentation. *Pattern Recognition*, 29(5), 859-871.
27. Bezdek, J.C.; Keller, J.; Krisnapuram, R.; and Pal, N.R. (2005). *Fuzzy models and algorithms for pattern recognition and image processing*. New York: Springer.
28. Liao, W.T. (2005). Clustering of time series data - a survey. *Pattern Recognition*, 38(11), 1857-1874.
29. Diniz, A.M.F.; Fontes, C.H.O.; Costa, C.A.; and Costa, G.M.N. (2015). Dynamic modeling and simulation of a water supply system with applications for improving energy efficiency. *Journal of Energy Efficiency*, 8(2), 417-432.
30. Pinto, J.C.; and Lage, P.L.C. (2001). *Mathematical methods in chemical engineering problems.* Rio de janeiro: E-papers.
31. Marques, C.A.X.; Fontes, C.H.; Embiruçu, M.; and Kalid, R.A. (2009). Efficiency control in a commercial counter flow wet cooling tower. *Journal of Energy Conversion and Management*, 50(11), 2843-2855.
32. Schiesser, W.E. (1991). *The numerical method of lines: integration of partial differential equations*. San Diego: Academic Press.
33. Ding, S.; Li, H.; Su, C.; Yu, J.; and Jin, F. (2013). Evolutionary artificial neural networks: A review. *Artificial Intelligence Review*, 39(3), 251-260.
34. Ahmadi, A.; and Mashoufi, B. (2012). A new optimized approach for artificial neural networks training using genetic algorithms and parallel processing. *International Review on Computers and Software*, 7(5), 2195-2199.
35. Farmaki, E.G.; Thomaidis, N.S.; and Efstathiou, C.E. (2010). Artificial neural networks in water analysis: Theory and applications. *International Journal of Environmental Analytical Chemistry*, 90(2), 85-105.
36. Magalhães, R.S.; Fontes, C.H.O.; Almeida, L.A.L.; and Embiruçu, M. (2011). Identification of hybrid ARX–neural network models for three-dimensional simulation of a vibroacoustic system. *Journal of Sound and Vibration*, 330(21), 5138-5150.
37. Santos, R.; Almeida Neto, J.F.; Campos, M; Embiruçu, M.; Fontes, C.H.O.; and Kalid, R.A. (2009). Multivariable correlation analysis with low sampling rate in output and its application in an LNG plant. *Journal of Petroleum Science and Engineering*, 66(1-2), 33-41.
38. Ferreira, A.M.S.; Cavalcante, C.A.M.T.; Fontes, C.H.O.; and Marambio, J.E.S. (2013). A new method for pattern recognition in load profiles to support decision-making in the management of the electric sector. *International Journal of Electrical Power & Energy Systems*, 53, 824-831.

39. Monedero, I.; Biscarri, F.; León, C.; Guerrero, J.I.; Biscarri, J.; and Millán, R. (2012). Detection of frauds and other non-technical losses in a power utility using Pearson coefficient, Bayesian networks and decision trees. *International Journal of Electrical Power & Energy Systems*, 34(1), 90-98.
40. Piatetsky, G. (2007). Data mining and knowledge discovery 1996 to 2005: overcoming the hype and moving from ‘‘university’’ to ‘‘business’’ and ‘‘analystics’’. *Data Mining and Knowledge Discovery*, 15(1), 99-105.
41. Alvisi, S.; Franchini, M.; and Marinelli, A. (2007). A short-term, pattern-based model for water-demand forecasting. *Journal of Hydroinformatics*, 9(1), 39-50.
42. Zhou, W.; Zang, L.; and Jiao, L. (2002). Linear programming support vector machines. *Pattern Recognition*, 35(12), 2927-2936.
43. Shvartser, L.; Shamir, U.; and Feldman, M. (1993). Forecasting hourly water demands by pattern recognition approach. *Journal of Water Resources Planning and Management*, 119(6), 611-627.
44. Vlachos, M.; Lin, J.; Keogh, E.; and Gunopolos, D. (2003). A wavelet-based anytime algorithm for k-means clustering of time series. *Proceedings of workshop on clustering high dimensionality data and its applications*, Riverside, United States, 23-30.
45. Emerson Network Power (2013). *Equipment Manual – drive inverter*. Emerson International Limited. Guangdong: Manufacturer trading company.
46. COELBA (Companhia Elétrica do Estado da Bahia) (2013). *Tabela de tarifa e preço final de energia elétrica.* Salvador: COELBA.