Parsimonious Modelling for Estimating Hospital Cooling Demand to Improve Energy Efficiency

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Abstract

Of all the different types of public buildings, hospitals are the biggest energy consumers. Cooling systems for air conditioning and healthcare uses are particularly energy intensive. Forecasting hospital thermal-cooling demand is a remarkable and innovative method capable of improving the overall energy efficiency of an entire cooling system. Predictive models allow users to forecast the activity of water-cooled generators and adapt power generation to the real demand expected for the day ahead, while avoiding inefficient subcooling. In addition, the maintenance costs related to unnecessary starts and stops and power-generator breakdowns occurring over the long term can be reduced. This study is based on the operations of a real hospital facility and details the steps taken to develop an optimal and efficient model based on a genetic methodology that searches for low-complexity models through feature selection, parameter tuning and parsimonious model selection. The methodology, called `GAparsimony`, has been tested with neural networks, support vector machines and gradient boosting techniques. Finally, a weighted combination of the three best models was created. The new operational method employed herein can be replicated in similar buildings with similar water-cooled generators.

Keywords: GAparsimony, parsimonious modelling, hybrid forecasting, thermal demand forecasting, cooling demand forecasting, Building Management System, air conditioning

1 Introduction

Hospitals require vast amounts of energy. In particular, hospital cooling systems that use chilled water for air conditioning (AC) or in other essential healthcare services and activities are what make hospitals some of the most energy-intensive consumers.

A common pitfall in many facilities is that after equipment is installed, it is not set up according to the expected level of energy efficiency. Using Building Management Systems (BMS) can improve energy efficiency and generate economic savings [1, 2]. Hospitals can decrease their energy use by 20% to 30% by implementing a BMS, adequately zoning for AC, using temperature measurement and control systems in different areas and planning proper-use schedules, and regulating the speeds of fans and water pumps [3].

The BMS used herein this study was implemented during the construction of the hospital under study in January 2008. The existing BMS, like most systems installed in buildings, is based on real-time control that utilizes information captured by sensors. Nevertheless, the control system generated more starts and stops than necessary in the liquid-cooled generators. This led to premature ageing in

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Vol. 30, No. 4,
Advance Access published 17 February 2021 https://doi.org/10.1093/jigpal/jzab008

the generators, higher cooling demand than necessary, frequent breakdowns and unnecessary thermal variations that did not correspond to the actual demand.

This study addresses these problems and improves the building's overall efficiency by creating a predictive model of the thermal cooling demand to help forecast the activity of the hospital's water-cooled generators (controlled by the BMS).

1.1 The search for parsimonious models

Several prior studies have already conducted related research into energy efficiency: analysis of building energy consumption in a hospital [4], forecasting cooling demand [5, 6] and short-term electrical load [7, 8]. These studies often utilize Gaussian processes [9], support vector machines (SVMs) [10, 11], artificial neural networks (ANNs) [12, 13], ANN applied to electrical consumption forescasting in a hospital facility [14], ANN comparison with random forest (RF) [15] and hybrid methods [16].

Forecasting applications are often based on regression models that are constructed with small databases gathered over a short period of time. In this case, however, the information was collected over more than 3 years, and during this period substantial improvements were achieved in the control of the cooling system. Therefore, the training database could be reduced to include just the final 21 months. In addition, the preprocessing strategy adopted measurements averaged by the hour, thereby considerably reducing the size of the training dataset and translating energy data to a common and understandable unit (in kWh).

In this kind of situation, seeking out low-complexity models (i.e. more parsimonious models), among various accurate solutions, is usually a reliable strategy for finding models that are robust against perturbations or noise. Parsimonious models aim to have a lower number of features, making them easier to maintain and understand [17, 18].

In recent years, there is an increasing need to create methods to automate and facilitate modelling processes with hyperparameter optimization (HO), and feature selection (FS), in order to reduce the human effort involved in these time-consuming tasks [19, 20] and therefore allow researchers to focus on other important processes like feature engineering or data mugging. Among the currently available methods, `GAparsimony` [21] is a genetic algorithm (GA) methodology that searches for parsimonious models and is specifically designed to work with smaller datasets. `GAparsimony` optimizes HO and FS by executing a parsimonious model selection, which is based on criteria that considers complexity and accuracy separately. Although `GAparsimony` performs quite well with HO, model selection with a complexity measurement based on the number of selected features has proven to be useful for obtaining more parsimonious solutions as compared to previous experiments [22].

`GAparsimony` has been extremely useful with classical machine learning methods, such as extreme gradient boosting machines (XGBoost), support vector regression (SVR), RF or ANNs [23], and has also been successfully applied in a range of contexts such as steel industrial processes [24], hotel room booking forecasting [25], mechanical [26] design and solar radiation forecasting [27]. The `GAparsimony` package for R has been available since July 2017 [28].

The present study presents a real application of `GAparsimony` that was utilized to create a parsimonious predictive model of a hospital's cooling demand. With the model created in this research, the amount of cooling water generated can be adapted to meet the actual demand expected for the day ahead; meanwhile, maintenance costs related to power generator breakdowns or ineffective starts and stops can also be reduced. Thus, the model can be useful for improving overall

TABLE 1. Chilled water production data.

	Electric power	Flow
Cooling unit with 3.5 MW of cooling power (per unit)	754.60 kW	—
Centrifugal chiller (EF1, EF2, EF3)	574.60 kW	
Group of evaporation pumps	45.00 kW	615.60 m3/h
Group of condensation pumps	90.00 kW	770.40 m3/h
Fans (3 units)	45.00 kW	
Cooling unit with 1 MW of cooling power (total)	317.50 kW	—
Screw chiller (EF4)	280.00 kW	
Group of evaporation pumps	7.50 kW	205.00 m3/h
Group of condensation pumps	15.00 kW	253.00 m3/h
Fan	15.00 kW	
Chilled water circuit	37.00 kW	2019.60 m3/h
Group of drive pumps (4 pumps)	9.25 kW	673.20 m3/h

energy efficiency, decreasing the electrical consumption of cooling systems and CO_2 emissions and minimizing maintenance costs.

2 Case study description

The San Pedro Hospital is located in the city of Logroño (Spain). It is the top hospital in the autonomous community of La Rioja and is part of the Spanish national public healthcare system.

The building covers an area of about 125,000 m^2. Most of the thermal generation, gas and high voltage installations are located in a separate building. Let us make note of the most energy-intensive medical services offered by this hospital: 600+ beds for hospitalization, a diagnostic imaging area, 23 operating rooms, emergency and consultation area with 21 boxes, hemodialysis, an intensive care unit, endoscopy, rehabilitation, laboratories, pharmacy, sterilization and other general services.

2.1 Description of the installations

The San Pedro hospital has a centralized cold-water production system for the high cooling demand of many healthcare services and for AC the building. The system consists of 4 chillers EF1, EF2, EF3 and EF4: 3 centrifugal units of 3.51 MW (*Trane CVFG* equipment) and 1 screw machine with 1 MW (*Trane RTHD* equipment) of cooling capacity. The system's electrical consumption data are described in Table 1.

The hospital's BMS is comprised primarily by controllers belonging to the Sauter *Sauter EY3600* family, which communicate with each other through the *novaNet* bus. The BMS is a SCADA application with a *novaPro Open 4.1.* environment. The server is located in the hospital data center.

Chilled water in a hospital has essential applications not only for human welfare but also for industrial and healthcare needs: e.g. AC operating rooms, out-patient surgery, intensive care, delivery rooms and emergency rooms. It is also utilized in radiology and diagnostic imaging equipment, scanners, mammography, etc.; for refrigeration storage such as in a blood bank, kitchen or pharmacy; for Kardex, pathological anatomy; and in the morgue, laboratories, data center racks, etc.

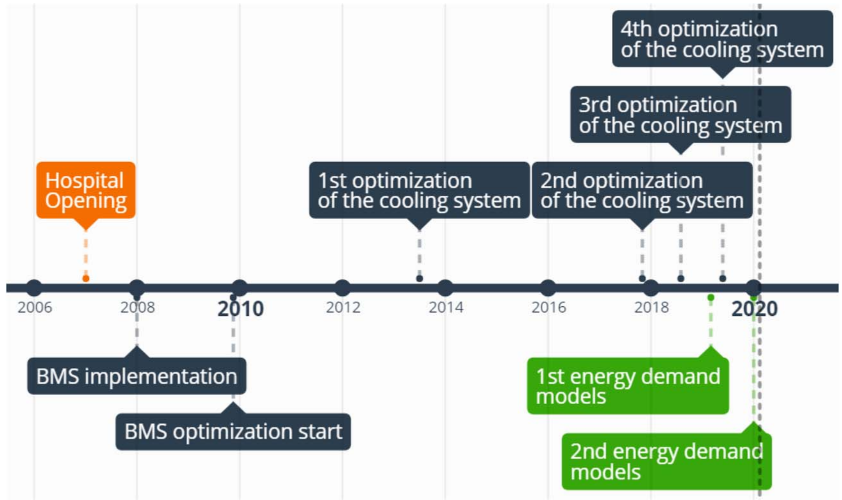

FIGURE 1. Case study timeline indicating remarkable improvements and model generations.

This article focuses on the study of a prediction model for a chilled-water system, given its significance for hospital services and its significant electrical consumption. Specific studies of hospitals have shown that the energy they use to generate chilled water exceeds 45% of the total energy necessary for building operations [3].

2.2 Optimization process for the cooling system

The existing problems detected in the cooling water system were the following:

- Uncontrolled starts and stops of the cooling generators, which negatively impact energy efficiency and can lead to significant breakdowns.
- Subcooling water-ring temperature below established set points, which is detrimental to energy efficiency.
- Overheating water-ring temperature above established set points, which can adversely affect health care processes.

Therefore, as a result of re-engineering and optimization using exploratory data analysis techniques and a full review of the installations, several actions were implemented following an established timeline, as can be seen in Figure 1, in order to improve the energy efficiency of the cooling system:

1. The first optimization of the system improved how the BMS calculated the temperature set point of the cold-water ring to cut down on the number of starts and stops in the chillers. This modification implemented a variable and graduated set point depending on the outside temperature.
2. The second optimization established a minimum work time for every generator of at least 1 hour and set up a cyclic order of use.
3. The third optimization implemented a variable setpoint for the ring temperature to be regulated according to the outside temperature as a ramp variable instead of as a stepped variable.

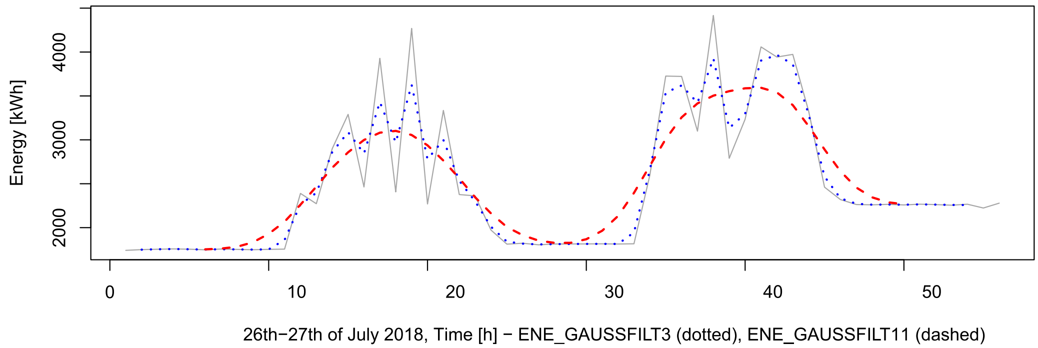

FIGURE 2. Filtering ENERGYKWHPOST with different Gaussian steps.

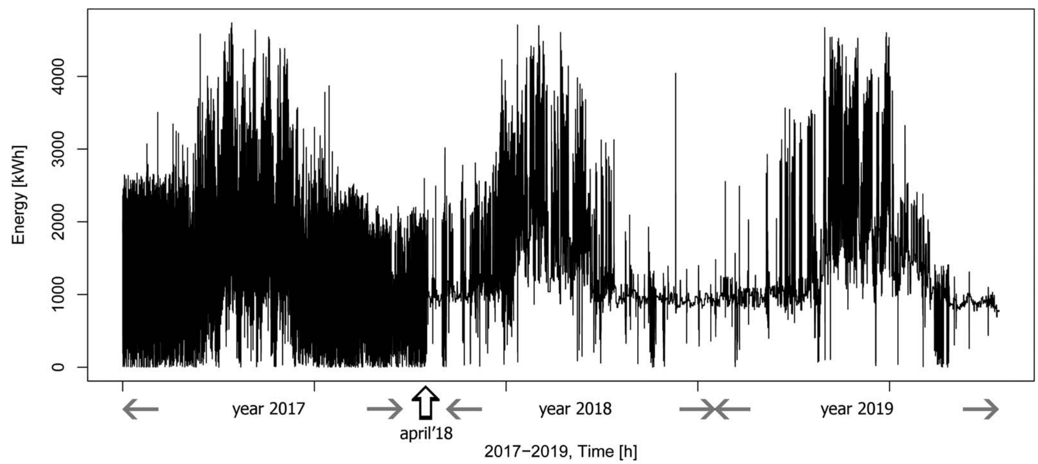

FIGURE 3. Evolution of ENERGYKWHPOST within the acquisition.

4. The fourth optimization consisted of installing frequency inverter systems in the EF4 generator. The frequency inverter (AFD) can regulate the speed of the compressor motor with a partial load. In the EF1, EF2 and EF3, which are centrifugal chillers, AFDs could not be installed, since they still have a modulation with the refrigerant charge. Communication hardware cards were installed in every generator to improve communication with the BMS.

The first energy demand models were calculated in March 2019 but inefficient behaviour was observed following the improvements implemented in April 2018 (see Figure 3). Therefore, the preprocessed data and the model itself needed to be updated to improve the model's accuracy. The second set of energy demand models were calculated in January 2020 after notable improvements were applied to the real system.

TABLE 2. Control system variables.

Short name	Description
EF1	EF1 - Status
EF2	EF2 - Status
EF3	EF3 - Status
EF4	EF4 - Status
TIMP	Cold Ring Drive Temperature [◦C]
TEXT	Exterior Temperature of Facilities Building [◦C]
TCONSIG	Calculated Setpoint of the regulation for Cold Production Drive [◦C]
TENEF1 to 4	Water temperature at the inlet of the EF1 to EF4 [◦C]
TSALEF1 to 4	Water temperature at the outlet of the EF1 to EF4 [◦C]

3 Dataset

3.1 Data extraction

The BMS installed in San Pedro Hospital recorded data through a measurement logger in the generation system (the BMS Sauter novaPro Open). Cooling energy was not measured by the system; thus, it had to be calculated and the data preprocessed. The variables extracted from the BMS generation system are listed in Table 2.

3.2 Data preprocessing

Data preprocessing involved the following actions:

1. Averaging measurements by the hour. The system recorded data whenever a variable altered its state or changed its measurement. The time difference between measurements could range from seconds to hours. Therefore, the data were divided into groups and presented by the hour.
2. Filling in missing values. Imputation of missing values was done by using the mean of the previous and next values.
3. Creating *Generated Thermal Power* and ENERGYKWHPOST features.
4. Filtering the target (ENERGYKWHPOST) to create a more stable variable.

The BMS lacked a thermal energy meter to save and measure the data. Nevertheless, both the instantaneous thermal power and the generated thermal energy could be obtained. Thanks to the other available variables in the measurement system and the fact that the pump flow in this system has a set value, thermal power could be calculated by the following formula:

$$Thermal\ Power = Flow * Thermal\ jump * Ce \tag{1}$$

where the thermal power is expressed in watts [W], the flow rate in l/h and the thermal jump in the chiller in degrees Celsius [◦C]. The specific heat of water is equal to 1.16 Wh/kg◦C and its specific weight is 1 kg/l.

The time difference between thermal power measurements is a known value, so thermal energy could be calculated. Considering that the minimum work time of generators is one hour, the chosen prediction variable was energy, ENERGYKWHPOST [kWh], rather than instantaneous power [kW].

Due to the previous adjustments made to remedy incorrect starts/stops and setpoints in the generators, the calculated variable of Thermal Energy (ENERGYKWHPOST) exhibited a sawtooth

TABLE 3. Data filtering of prediction variable, year 2018.

Filter	ENERGY [kWh]	RMS	MAE
ENERGYKWHPOST	10.266.880,7	0	0
ENE_GAUSSFILT3	10.266.843,3	166,4	37,4
ENE_GAUSSFILT5	10.266.883,6	278,3	2,9
ENE_GAUSSFILT9	10.266.911,1	328,2	30,4
ENE_GAUSSFILT11	10.266.889,9	338,5	9,2

TABLE 4. Attributes selected for the forecast model.

Variable	Description
ENE_GAUSSFILT11	Target
month	Month of measurement
day_of_week	Day of the week
Is_holiday	Boolean variable for holiday
TIMP	Instant impulsion temperature
TEXT	Instant exterior temperature
TMEAN	Average daily temperature
TMAX	Maximum daily temperature
TMIN	Minimum daily temperature

graph, as can be seen in Figure 3. Such results could later lead to an inadequate learning process; thus, the thermal energy was filtered in order to smooth out ENERGYKWHPOST, as can be observed in Figure 2.

Different filters were tested, but the Gaussian function was the method selected to filter and smooth thermal energy. This method was chosen for it slow error rate, as shown in Table 3, and because the accumulated energy in the tested year was similar to the real amount of accumulated energy. ENERGYKWHPOST was compared with different filters (see Figure 2). A Gaussian filter with a window size of 11 (ENE_GAUSSFILT11), represented by a dashed line, displayed a smoother curve without distortion as compared to the dotted line of a Gaussian filter with a window size of 3 (ENE_GAUSSFILT3). Therefore, ENE_GAUSSFILT11 was eventually selected as the target. This feature was considered close to the hospital's energy demand, which primarily depends upon weather conditions and the use of the facilities.

3.3 Final dataset

The attributes selected were shown in Table 4.

4 Parsimonious modeling

The search for parsimonious models was performed with the `GAparsimony` methodology. For this purpose, three popular algorithms were used: SVMs with RBF kernel, ANNs and extreme gradient boosting machines (XGB). All the experiments were implemented with the `GAparsimony` [29] package in R programming language.

4.1 GAparsimony settings

`GAparsimony` optimization extracts the algorithm's parameters and the selected input features from the λ_g^i chromosome for each individual i of the generation g.

Chromosome λ_g^i was defined for each method as follows:

$$\begin{aligned} SVR(\lambda_g^i) &= [cost,\ gamma,\ epsilon,\ Q] \\ ANN(\lambda_g^i) &= [size,\ decay,\ num\_epochs,\ Q] \\ XGB(\lambda_g^i) &= [subsample,\ colsample\_bytree, \\ &\quad max\_depth,\ alpha,\ lambda,\ Q] \end{aligned} \tag{2}$$

where the values correspond to the algorithm's parameters except the last one, Q, which is a vector of probabilities for selecting each input feature j when $Q_j \geq 0.5$.

`GAparsimony` uses root mean squared error (RMSE) for evaluating individuals within the optimizing process, $RMSE_{val}$. RMSE measured with the test database, $RMSE_{tst}$, is used to check the model's generalization capability. Finally, model complexity reflects to the number of selected features N_{FS}. This complexity performed well in previous experiments with `GAparsimony`.

The genetic optimization process in `GAparsimony` is defined with a population of 40 individuals evaluated in 100 generations but with an early stopping criteria if $RMSE_{val}$ does not improve in 20 iterations. The selection process uses 20% of the best solutions and is based on a two-step process: first, models are ordered by $RMSE_{val}$, next, individuals with similar $RMSE_{val}$ are reordered according to complexity. The objective is to promote parsimonious solutions (with lower complexity) to top positions. In this case, two $RMSE_{val}$ are considered to be similar if their $RMSE_{val}$ absolute difference is lower than a ReRank parameter which is defined by the user. In this study, after several experiments, $ReRank = 0.1$ achieved a satisfactory trade-off between complexity and $RMSE_{val}$.

In order to start the GA process with a high percentage of input, 90% of the features were selected from the first population. Finally, mutation was defined by the number of most elite individuals that were not mutated (2), the probability of mutation in the model's parameter in the chromosome (10%) and the probability of a feature having the value of 1 if the feature is selected to be mutated (10%). This parameter was set to a low value of 10% to facilitate the reduction of input features in the following generations.

5 Results and discussion

5.1 Initial energy-demand models

The first energy-demand models were trained with the dataset from the period between January 2017 and February 2018. The validation database corresponds to the even weeks between March 2018 and February 2019 and the testing database with the odd weeks of that same time period.

Surprisingly, `GAparsimony` with SVR was capable of obtaining a parsimonious model with only 3 attributes and acceptable validation and testing errors. To some degree, an explanation for this can be found in the improvements (applied) in the control process after the first acquisition period that averaged out 'the noise' thereby reducing the differences between the training database and the validation/testing data.

TABLE 5. Best individual for each algorithm obtained with `GAparsimony`.

		SVR	ANN	XGB
	$RMSE_{val}$	294.9	327.4	347.8
	$RMSE_{tst}$	342.4	363.3	371.1
VARS	month	1	1	1
	day_of_week	0	1	1
	Is_holiday	0	1	0
	TIMP	0	1	1
	TEXT	1	1	1
	TMEAN	0	0	0
	TMAX	0	1	0
	TMIN	1	1	0
	Complexity	3	7	4

The SVR algorithm obtained the best validation and testing error with only 3 attributes: month (month) and the external (TEXT) and minimum temperatures (TMIN). ANN came in second place with 7 features and, finally, XGB which selected only 4.

Table 5 shows the validation and testing errors and the final selected features for the best model from the last generation with SVR, ANN and XGB, respectively.

5.2 Second energy-demand models

In order to create the second set of energy-demand models, the data recorded between 2017 to March 2018 were removed due to the significant optimizations implemented in the cooling system during this period. Figure 3 shows the high level of noise produced by inefficient starts and stops prior to April 2018. Thus, the second model was trained and tested with the information collected from April 2018 to December 2019. The training dataset corresponds to the period between January 2018 and February 2019. The validation database corresponds to the even weeks between March 2019 and December 2019 and the testing database to the odd weeks of the same time period.

`GAparsimony` was used again to choose the best models among the different algorithms, to adjust the internal parameters, and develop the FS as well. Errors, parameters and selected features are shown in Table 6. In the table below, it can be observed that the error values are better than those obtained with the initial energy-demand model.

SVR model: the best SVR model was obtained with 4 features: month (*month*) and the external (*TEXT*), averaged (*TMED*) and maximum (*TMAX*) daily temperatures. Figure 4 shows, in white and grey box-plots, the $RMSE_{val}$ and $RMSE_{tst}$ SVR evolutions for the most elite population of the best `GAparsimony` iteration. In this case, `GAparsimony` converged in 7 generations.

ANN model: the best ANN model converged in 4 generations with 5 features: month (*month*), if the day was a bank holiday (*Is_holiday*), ring temperature (*TIMP*) and the external (*TEXT*) and averaged (*TMED*) daily temperatures. ANN errors were only slightly superior to those of the SVG model.

XGB model: the best XGB model was optimized after 4 generations with 4 features: month (*month*), day of week (*day_of_week*) and the external (*TEXT*) and averaged temperatures (*TMED*) of the day.

TABLE 6. Best models with results, complexity, generation and parameters.

	SVR	ANN		XGB	
$RMSE_{val}$	231.9	233.2		239.8	
$RMSE_{tst}$	260.9	268.2		267.7	
month	1	1		1	
day_of_week	0	0		1	
Is_holiday	0	1		0	
TIMP	0	1		0	
TEXT	1	1		1	
TMED	1	1		1	
TMAX	1	0		0	
TMIN	0	0		0	
Complexity	4	5		4	
Generation	V7	V4		V4	
Parameters:					
expcost	0.42	*size*	21	*subsample*	0.70
gamma	0.20	*decay*	45.0	*colsample_bytree*	0.91
epsilon	0.09	*maxit*	637.8	*max_depth*	2
				alpha	0.03
				lambda	0.31

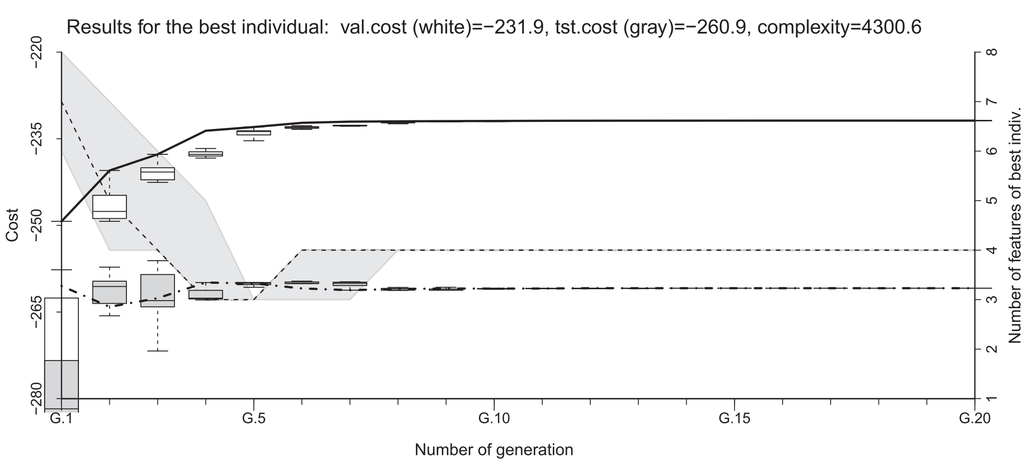

FIGURE 4. Evolution of the errors of the most elite solutions for SVR algorithm. White and grey boxplots represent the $RMSE_{val}$ and $RMSE_{tst}$ evolutions, respectively, and continuous and shaded lines indicate the best individual of each population. The grey area covers the maximum and minimum number of features N_{FS} (right axis).

Ensemble model: finally, the best SVR, ANN and XGB were combined to obtain an ensemble model with an enhanced performance. The process was conducted by weighting the predictions of

TABLE 7. Ensemble validation and test errors versus single models.

	SVR	ANN	XGB	HYBRID
$RMSE_{val}$	231.9	233.2	239.8	224.82
$RMSE_{tst}$	260.9	268.2	267.7	257.49
complexity	4	5	4	7

each learner as follows:

$$Ensemble\_Model = (w1 * SVR + w2 * ANN + w3 * XGB)/3.0 \tag{3}$$

In order to determine the weights, an optimization of $w1$ and $w2$ was performed by reducing the $RMSE_{val}$ obtained with this equation and the previous model validation predictions. In this process, $w3$ was internally calculated as $w3 = 3 - w1 - w2$.

The optimum model was comprised by the following weights:

$$Ensemble\_Model = (1.36 * SVR + 1.41 * ANN + 0.23 * XGB)/3.0 \tag{4}$$

Table 7 shows the $RMSE_{val}$ and $RMSE_{tst}$ of the weighted combined model versus single models. Error values are slightly better in the ensemble model than the best single model (SVR model) (see Figure 5). Complexity increases because of the number of features needed as input for the models comprising the hybrid model; however, the variable of minimum daily temperature (TMIN) was not utilized in the final model.

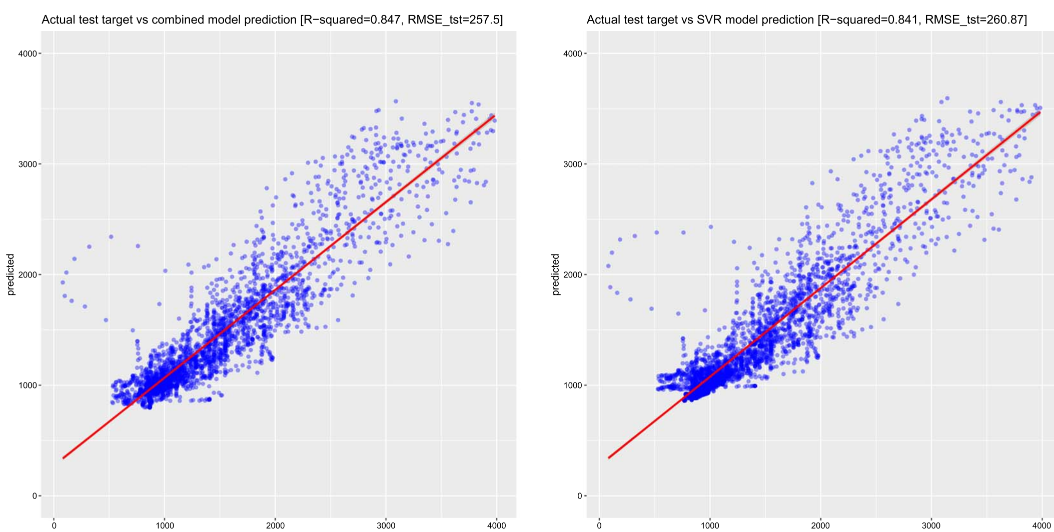

FIGURE 5. Ensemble and SVR combined predictions.

6 Conclusions

This study has demonstrated that `GAparsimony` is an effective and advanced method for selecting the best parsimonious model among different forecasting methodologies and for adjusting internal parameters and selecting the best features as well.

The analysis conducted in this study took place over the course of more than 3 years and demonstrates the imperative need to optimize cooling systems before effective prediction models can be created, as they would then be able to learn from balanced system data. The models obtained have similar errors and use similar features, and this fact demonstrates that the prior optimization process was a worthwhile endeavor.

The final ensemble model which combines the three best parsimonious models will be easy to maintain because information is directly available from sensors and meteorological forecasting. The error rate has been significantly reduced compared to the initial models. And, although it is not an insignificant error, it does facilitate forecasting that will allow control engineers to program the chillers to supply the maximum demand for the coming hours. In addition, with the improvements made in modulating the cooling system, the system will be able to buffer variations not programmed into the day-to-day activity.

The next step in this line of research is to implement the ensemble model within the BMS decision software and then test and track the real response in order to validate and measure the results.

Acknowledgements

We are greatly indebted to *Banco Santander* for the APPI17/04 and REGI2018/43 fellowships. This study used the Beronia cluster (Universidad de La Rioja), which is supported by FEDER-MINECO grant number UNLR-094E-2C-225.

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Received 10 February 2020