Mather Thesis

Optimizing Energy Consumption on a Municipal Building

Miguel Gameiro
miguelgameiro@tecnico.ulisboa.pt
Instituto Superior Técnico

***Abstract*—HVAC (Heating, Ventilation and Air Conditioning) systems are critical in modern human activity. The increasing demand for heating and cooling applications increases the number of HVACs. Based on many studies, these are some of the most energy consumer systems worldwide. An HVAC is, usually, a long term investment. It is installed having in account specific necessities of the building. However, one can find that often HVAC from commercial consume energy in excess.**

A common solution found on literature is to use model predictive control. However, these solutions maybe not be viable economically. Here, it is presented an optimal control framework for the optimization of HVACs. This framework uses data-driven models to predict the system dynamics in the chosen scenario.

This dissertation shows a start to end case study on Cascais Center, where it is applied an optimal control framework, aiming to improve energy costs and thermal comfort. In this case, the optimized variable is the chiller temperature setpoint, using NSGA-III and PSO meta-heuristics. The models are base on data-driven predictors, the NARX Neural Network and Takagi-Sugeno, with improved feature extraction achieved by using PCA. Hence, it is presented a methodology for variable selection and feature extraction. The predictors performance is improved based on data analysis considerations. The results a need for further work on data acquisition, prediction robustness and thermal comfort estimation.

Keywords: HVAC, optimization, optimal control, meta-heuristics, data-driven models, PCA

I. Introduction

A. Motivation

HVAC (Heating, Ventilation and Air Conditioning) systems are critical in modern human activity. Society has becoming more dependent on temperature control applications for reasons like food refrigeration, computation and networking, more complex industry and manufacturing processes. In all these cases, the need for these systems is increasing and becoming more important in energy consumption pattern around the world. This reason makes HVAC systems one of the most interesting to optimize.

The worldwide electrical energy demand increases early, requiring more and more electrical energy production. In part because of the appearing of new and more powerful applications but also because of its preference over other energy forms. There is a common known world's effort in reducing electrical energy demand, implying a need of optimizing the actual usage.

Australia's electrical energy regulatory and the University of Michigan estimated the typical energy consumption pattern in office buildings of Australia and residential buildings of United States of America shown in Figure 1.

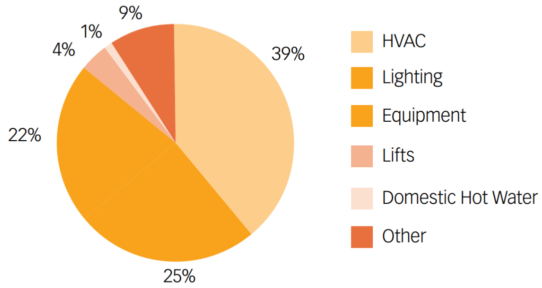

Fig. 1: Office buildings typical consumption in Australia [1]

The HVAC usage is the highest energy consumption application, with 39%. This consumption can't be isolated, the increasing usage of another devices can influence the thermal load, for example, in an office building computers are extra thermal loads for the cooling system since they produce heat.

In commercial buildings, HVAC systems are very important in keeping the thermal comfort and the air quality inside. Its main functions are to control temperature, humidity, air renewal, filtration of airborne particles and air movement inside. All these factors influence people's perception in a non-linear way, having opposite effects for different people.

In a consumption optimization perspective it is useful to have a centralized model in charge of controlling the operation parameters. This allows making use of the most important principal in a system optimization strategy: consume just the minimum amount, not an amount needed for a general case of the same type. This is the reason for using a data dependent approach for optimizing the system usage.

B. Objectives

The objective for this thesis is to study a methodology to improve a legacy HVAC system usage in terms of electrical energy costs and thermal comfort provided. The idea is to find an optimized chiller setpoint which decreases the energy consumption and increases the thermal comfort.

II. Cascais Center

A. Building

The Cascais Center is a building situated in Cascais city. The building has 7 floors, several public service stores and some offices, which belong to the city. This topology of building concentrate a big amount of people, some working there, some using the services provided. A photo of Cascais Center building is shown in Figure 2.

Fig. 2: Cascais Center photo [2]

At bottom floors there are many common areas. There are 3 stores: Loja do Cidadão, National Insurance and CTT (Correios de Portugal, SA), a cantine, a computer team open-space and wide space halls and corridors. In these floors, there is more people and movement getting in and out of the building. These spaces are used by workers and also clients for these stores. At top floors there are office cabinets for non-public attendance workers. There are less density of people, separated by different divisions.

B. Thermal Zones

The building has an heterogeneous density of people inside and on space distribution, implying an heterogeneous influence on HVAC system dynamics. During dissertation, the focus was higher on two commercial spaces, the Loja do Cidadão and the Social Security store.

There are two important concepts to define first, based on [3] reference definitions. The concepts of thermal zone and thermal space. A thermal zone is a part of the building controlled with a single sensor.

Applying these concepts to the Cascais Center case, the interest is to make the thermal zones of the new system roughly coincide with the thermal spaces identified empirically inside the chosen stores. In other words, the Social Security store is one thermal zone and Loja do Cidadão can be divided in two thermal zones, with a sensor closer to the air fan and one closer to people service desk.

Loja do Cidadão and Social Security store are relatively different when it comes to occupancy dynamics. The office hours on both stores is presented on Table I.

TABLE I: Cascais Center stores schedule

Store	Week Day	Schedule
Loja do Cidadão	Monday - Friday	09h00m - 18h00m
Social Security	Monday - Friday	09h00m - 16h00m

C. HVAC System

The main parts of the HVAC system from Cascais Center are the chillers and pumps, the air handlers, and the fans. The chillers and pumps part are common for all building thermal zones. They define the operation mode for the system, heating or cooling. These components are presented in Table II.

TABLE II: Nominal power for HVAC modules

Module	Nominal Power Heating	Nominal Power Cooling
Heat/Cool Chiller	219.7 kW	231.0 kW
Cool Chiller	-	150.0 kW
Air Handler	13.2 kW	17.0 kW
New Air Handler	09.9 kW	44.8 kW
Fans	54.0 W/97.0 W/111 W	

Notice the indicated values are the nominal power ones, not fixed ones. Changing conditions or commands change the energy consumption. For each chiller, there is one setpoint for the interior water temperature, which later influences the interior building air temperature.

D. Data Acquirement

To produce a data-driven model, it was acquired the HVAC system energy consumption and three interior temperatures for the defined thermal zones, with a 5 minutes sampling period, with a 1 hour sampling period, and meteorological data. The HVAC energy was acquired by using Fluke 1735 and the interior temperatures by using a TinyTag Tk-4000. The meteorological data was gently given by meteoblue website [4]. The acquisition periods are presented in Table III.

TABLE III: Periods of data acquisition

Reference	First day	Last day	Operating Mode
April 2017	08/04/2017	16/04/2017	Cooling
September 2017	12/09/2017	19/09/2017	Cooling
January 2018	23/01/2018	05/02/2018	Heating
April 2018	27/03/2018	08/04/2018	Heating
June 2018	19/06/2018	02/07/2018	Cooling

These acquirement periods form a dataset with 30 days on heating operating mode and 27 days on cooling operating mode. During the heating period, the chiller setpoint values were 39^oC, 41^oC and 42^oC. On cooling period, the chiller setpoint values tested were 7.5^oC, 8.0^oC, 8.5^oC and 9.5^oC.

III. Optimization

The optimization is the mathematical method to calculate a chiller setpoint based on given conditions. An optimization method bases its principle in finding either a minimum or a maximum for certain set of cost values, based on some criteria which define dynamics of these costs. The costs values are a mathematical description on the objective to be optimized. By doing this, the result is to find which criteria may lead to a better performance on the selected objectives to optimize.

A. Cost Function

A cost function is a mathematical way to describe the objectives to achieve. In fact, optimizing the HVAC usage is to minimize the energy consumption while maximizing the thermal comfort costs. The cost function for these two objectives will give a 2-dimensional value from the inputs selected as a metric of how well accomplished are the objectives.

1) Electrical Energy Cost: The electrical energy cost is a straightforward calculation once the power evolution is predicted. It is only considered the active energy price since the power factor is 0.99 on average, due to an installed power factor compensation. The energy cost is

$$C_E = \sum_{k=1}^{N} \left[p_a[q_a(k), t(k)] \; E_a(k) \right] \tag{1}$$

where p_a represents the tariff price of energy for the active power part, q_a represents the year quarter, t represents the time of day and E_a the energy considering just the active power part. This is the first objective cost. The value of C_E is intended to be minimized after running the algorithm.

2) Thermal Comfort: For the thermal comfort objective, the case is rather more complex. Thermal comfort depends on a lot of different variables, which are hard to measure and easy to have its value changed from day to day. One important factor in measuring thermal comfort is to measure a temperature expectation. In Figure 3 represents an interval for temperature expectation based on exterior temperature.

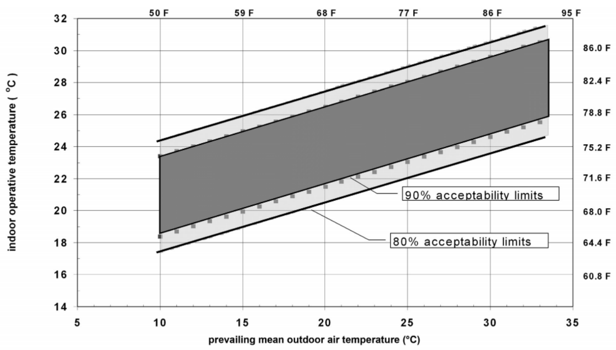

Fig. 3: Predicted percentage of dissatisfied as a function of exterior temperature [5]

The reference temperature is considered do be the middle point on darker grey rectangle for the actual exterior temperature. First, it is defined a comfort value for each sample. As a first approach, the model is based on an absolute difference to a reference temperature, described by

$$C_{TS}(k) = \min \left\{ |T(k) - T_{ref}| \; h_{store}(k), 3 \right\} \tag{2}$$

where $T(k)$ is the actual temperature inside, T_{ref} is the reference temperature for the room, $h_{store}(k)$ represents the state (opened or closed) of the store in a boolean form and the value 3 is the saturation chosen.

For optimization purposes, it is easier to use the absolute value, has a direct scale for comfort where 0 is the most comfortable case and 3 the most uncomfortable one. The expression for the thermal comfort estimator is

$$C_T = \text{mean}(C_{TS}) + \text{std}(C_{TS}) \tag{3}$$

calculated as a function of C_{TS} within a defined time horizon. The average of the thermal comfort is the base metric for system performance in this field. But for a period much longer than the thermal constant from the rooms can be achieved in a number of different temperature variations. The standard deviation of the thermal comfort evolution measures how much it deviates from the average during time. The global thermal comfort estimator, C_T, takes into account these two factors to better model it and achieve better results.

B. Meta-heuristic Algorithms

The best suited models for this dissertation project are meta-heuristic ones. Meta-heuristics are mostly based on observed nature behavior in different situations [6]. These methods provide a derivative free optimization, a necessary condition when dealing with data-driven models. In this dissertation, the used methods are genetic algorithm, with NSGA-III, and particle swarm optimization, with MOPSO. Both implementations are available at *yarpiz* website [**?**].

C. Pareto Optimization

When using meta-heuristics for multi-objective cost functions, the result is to have a cloud of solution points. There is a need to select the best solution. The Pareto optimization is a method to find a smaller set with the most efficient solutions, a Pareto frontier, which have the best compromise in between objectives. From this smaller step, the optimal solution is selected with the case study in mind, as described on chapter VI-B.

IV. Observers

The cost function for the optimization process depends upon the energy consumption and the interior temperature. The chiller setpoint is a parameter each of these variables, and consequently, to the cost value itself. The observers keep the optimization results physically feasible. The method is to use machine learning techniques, based on supervised learning, to predict the influence of the selected chiller setpoint on cost values.

A. Data Pre-Processing

The acquired raw signals, are in different timetables and with different sampling frequencies. The linear interpolation is used in order to synchronize it in a unified timetable, useful into modeling.

Other variables are not acquired in a sensor form, mostly related to schedules and routines of people working there or clients there. There is a need to create a signal format for using this information. For each store there is a boolean value on each sample, equivalent to the stores' states *opened* and *closed*. The week day is converted to a variable which can assume 7 states, representing the 7 days of the week. The schedule from air handlers follow the same format as store schedule with one boolean value for each sample, representing the states ON and OFF. The chiller setpoint is a real number value on each sample.

B. Observer Structure

The observer structure defines the sequence of calculations needed for predicting the output based on input information. The structure of the observer includes the predictive model, but may also include some amount of pre-processing, depending on principles of the model. On a dynamical system, the usual differences in between observers are in number of inputs and outputs and the amount of delay on input or previous output information used on each sample prediction.

1) Operating Mode: Nothing has a higher impact on HVAC system dynamics than the selected operating mode. The system reacts differently to the environment when it is either heating or cooling. The hierarchy of importance on each part of information extracted is a different one for each operating mode. This way, for each operating mode, the observers are implemented separately.

2) Prediction Model: The prediction model is the mathematical model which allows the estimation of a future value based on past, either from the other variables or the variable being observed.

The first model is NARX Neural Network (Nonlinear Autoregressive Network with Exogenous Inputs), the most widely used model for energy consumption optimization in HVAC systems on state of art scientific papers. The diagram of the NARX model is presented in Figure 4.

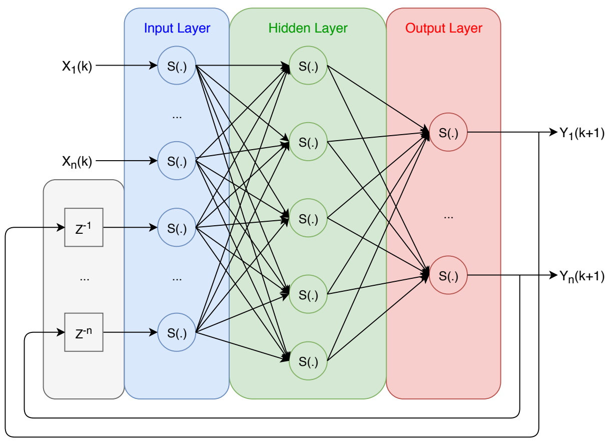

Fig. 4: NARX model diagram

The NARX Neural Network model has 4 different functional parts, represented in the diagram with 4 colored round-edge rectangles. In this Figure 4 the delay blocks (represented with Z^{-m}, $m \in N$) are connecting just one output, but in real case they are connecting every output. The S(.) represents the sigmoid function, applied after the sum on all inputs. This is a tentative to not overload the image with arrows crossing each other. The used implementation of NARX Neural Network is from a well tested mathematical software.

The second model considered is Takagi-Sugeno model. The choice of this model for this dissertation was done because the model is more robust to data uncertainty than NARX Neural Network model. The diagram of the model implementation is presented in Figure 5.

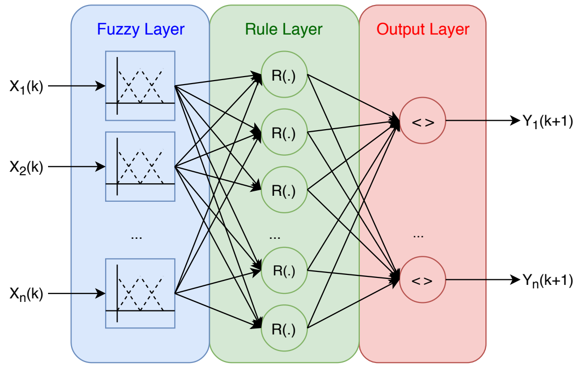

Fig. 5: Takagi-Sugeno model diagram

Takagi-Sugeno model has 3 functional parts, represented with 3 colored rectangles. At neuron's output an activation operation, in here referred as rule, which can be either AND or OR operation on the variables. The output layer makes the defuzification operation. The defuzification operation chosen in here is base on the center of mass operation, applied on rule layer output for each neuron in output layer. The used implementation of the Takagi-Sugeno model was developed for the dissertation project, using a mathematical software.

3) Input Variables: The first challenge for good observers modeling is a good set input variable choice. The input variables are chosen by the quantity and quality of information which can be extracted to describe system dynamic behavior. A more intuitive way to think is to choose them by wider fields of behavior. For this dissertation, the chosen fields are meteorological data, to characterize dynamics related to the weather variations, routine data, to characterize the ones related with people schedules and some typical client behavior and system command, to characterize the user configuration input. The process for choosing the inputs is summarized in Table IV.

Notice that there are some fundamental differences in these fields. Meteorological and human routine related variables are variables which characterize the environment around. Further, in this document, they are referred as environment variables. The last field is related to user input, referred as command variables.

The variables are used in a normalize form during supervised learning. Table V presents the range considered in each variable for normalizing into a range of [0,1].

Taking into account the chosen variables, presented on Table IV, the inputs have dimension 12. For dimensional reduction, it is used PCA (Principal Component Analysis) algorithm. The dimension after applying the algorithm is chosen based on a compromise between the amount of information needed to preserve and the complexity of the resulting observers. The considered dimension in this dissertation is 3 principal components. The algorithm is applied individually for heating and cooling operating modes.

During dissertation, the observers presented the best results with 3 principal components. Hence, the input for the observers is constituted by 3 principal components, to characterize the meteorological and human routine information, and

TABLE IV: Information extraction variables selection

Variables	Reason
Characterize meteorological environment	
Exterior temperature	Exterior temperature is directly related to the needed energy for maintaining the desired temperature in each part of system.
Solar radiation	The solar radiation is an image for predicting future heating on both interior and exterior temperature.
Humidity	Humidity is one of the most important variables for the human thermal comfort. It can describe also part of HVAC system's fluid behavior.
Wind speed	Wind speed can have influence on system thermal dynamic, mostly on Winter, since a major part of it is outside on the roof. Also, some of the visits to the building showed some store windows opened.
Characterize human routines	
Time of day	The time of the day can be rough estimation to the usual store occupation, mainly when combined with other variables such as week day.
Week day	The week day is the most important variable in characterizing the main routines from stores. It includes information about cyclic behavior, typical from commercial places. This cyclic behavior includes information like differences on daily dependent attendance or clients preferred days.
Store schedules	The store schedule is a boolean variable for each store with states open and close. It is important in predicting more accurately the dynamic differences between stores, due to their different schedules.
Characterize HVAC system commands	
Chiller setpoint	The chiller setpoint is the user defined temperature for the fluid chiller used on chiller. It is the optimized variable.
Air Handler schedules	The air handler schedule is represented by a boolean variable for each of them, with ON and OFF states. These schedules influence on the degree of chiller action on temperature and evolution of energy consumption.

TABLE V: Normalization limits for considered variables

Variables	Minimum value	Maximum value
Time of day [HH]	0	24
Exterior temperature [^{o}C]	0	50
Solar radiation [W/m^2]	0	1000
Humity [%]	0	100
Wind speed [km/h]	0	75
Day of the week	1	7
Interior temperature [^{o}C]	15	35
Store schedule [Close/Open]	0	1
Hot chiller setpoint [^{o}C]	35	45
Cold chiller setpoint [^{o}C]	5	15
UTAs schedule [OFF/ON]	0	1

the normalized command variables, making a total of 7 input variables.

4) Dataset Partition: The results achieved when using data-driven modeling strongly depends upon the dataset partition. The dataset partition is the division made on the available data to the train the model, validate it and test it. In this case, the idea is to model dynamic systems, which make a division in blocks a better suited one than the random division. An usual rule of thumb, followed in this dissertation, is to divide roughly in a quota of 70% for training set and 15% for validation and test sets. In this dissertation, for a better division, it is used prior information. This way, there is a higher number different scenarios in each set, which improves the modeling results.

V. Observer Implementation

There are 6 observer implementations considering both operating modes. Two of them for predicting power and other four for predicting temperatures on the three chosen thermal zones.

A. Power Observer

The power observer aims to predict the average power signal of the HVAC. The energy consumption is calculated using the power prediction by multiplying it by the sampling period.

1) Performance Metric: Though the power observer predicts average power usage, the objective is to predict energy consumption and its associated costs. Therefore the predicting performance on power observers are based on how well they predict these variables. These metrics are applied on observers for both predicting models and presented in Tables VI and VII.

TABLE VI: NARX observer results table

Operating Mode	Variable	Real Situation	Observer Prediction	Error
Heating	**Energy [kWh]**	36777	37128	0.96%
	Cost [€]	353.26	354.92	0.47%
Cooling	**Energy [kWh]**	34535	35377	2.44%
	Cost [€]	340.62	339.72	-0.26%

The real and predicted energy and energy cost are compared on test set for both operating modes. The errors show a good adaptation to data on test set. As expected, the errors are higher on energy than on cost, due a slower variation when compared to the sampling frequency.

TABLE VII: Takagi-Sugeno observer results table

Operating Mode	Variable	Real Situation	Observer Prediction	Error
Heating	**Energy [kWh]**	36777	41079	11.70%
	Cost [€]	353.26	395.87	12.06%
Cooling	**Energy [kWh]**	34535	44134	27.79%
	Cost [€]	340.62	425.04	24.78%

Based on the results from Table VII, the observer using Takagi-Sugeno prediction model is not able of correctly of predicting the the energy consumption on the HVAC.

On both prediction models, the results are better on heating mode than on cooling mode. One reason is that on on heating mode data, there is a smaller variety of different situations than on the cooling mode. The 27 days on heating mode data are divided in two different months with 3 different chiller setpoints. The 30 days on cooling mode were acquired on 3 different months of the year in two different weather seasons. During these acquisitions, 4 different chiller setpoints were tested. Another reason is that the cooling mode depends less on the setpoint considered, since the second chiller may be working in parallel during this time, mainly during Summer.

2) Chiller Setpoint Sensitivity: The sensitivity to the chiller setpoint variation is an influential result on the observer performance considering th chiller setpoint is defined as the optimized variable. For evaluating the chiller setpoint extrapolation, it is chosen a typical day, from which the results are compared. On Tables VIII and IX it is presented the variation on the energy consumption and cost predictions for different chiller setpoints.

TABLE VIII: NARX Neural Network power observer sensitivity to chiller setpoint

Heating			Cooling		
Setpoint [^{o}C]	Energy [kWh]	Cost [€]	Setpoint [^{o}C]	Energy [kWh]	Cost [€]
35.0	15515	148.64	05.0	5283	51.17
37.5	10399	101.03	07.5	5524	53.35
40.0	5102	49.27	10.0	9625	93.43
42.5	7740	75.44	12.5	9626	94.54
45.0	5210	50.08	15.0	9426	94.29

The cost sensitivity to the chiller setpoint variation shows a behavior opposite to the expected one in Table VIII. For the heating mode, the cost is expected to increase when the setpoint increases. On cooling mode, the expected is for the cost to increase when the setpoint decreases. This is possibly a result of a bad modeling extrapolation for other setpoints, not present in the dataset. The cooling mode shows a more notorious example of the situation described. There is a cost step evolution on middle range values and a saturation on values around the frontier setpoints.

TABLE IX: Takagi-Sugeno power observer sensitivity to chiller setpoint

Heating			Cooling		
Setpoint [^{o}C]	Energy [kWh]	Cost [€]	Setpoint [^{o}C]	Energy [kWh]	Cost [€]
33	6231	60.09	05	8700	84.58
36	6150	59.31	08	8867	86.26
39	6259	60.38	11	8607	83.65
42	6807	65.64	14	8395	81.59
45	6420	61.92	17	8490	82.53

On Takagi-Sugeno power observer the tendency is the same. The sensitivity of the energy consumption to the chiller setpoint variation does not follow the expected variation. For both cases, there does not seem exist such an influence of the chiller setpoint on prediction value.

B. Temperature Observers

The temperature observer from Social Security store predicts the ambiance temperature inside. The temperature observer for Loja do Cidadão predicts the air outputs temperature and the ambiance temperature. The observers from different stores are trained separately because their temperature is controlled on different air handlers on different air handlers, which implies a different temperature reference in the room.

1) Performance Metric: To evaluate the performance of temperature observers, a set of empirically metrics were chosen. These are AAE, average absolute error, ESTD, error standard deviation, and MAE, maximum absolute error. The values in percentage of the normalized to the temperature of 25^{o}C. The implementation results are presented on Table X and XI for both prediction models.

TABLE X: Performance metrics for Social Security store temperature observer

Metric	NARX Neural Network				Takagi-Sugeno			
	Heating		Cooling		Heating		Cooling	
	[^{o}C]	[%]	[^{o}C]	[%]	[^{o}C]	[%]	[^{o}C]	[%]
AAE	0.94	3.74	1.11	4.45	1.06	4.23	1.23	4.93
ESTD	0.91	3.64	1.33	5.34	1.03	4.10	1.69	6.76
MAE	2.66	10.66	3.35	13.40	3.33	13.33	5.13	20.52

The standard deviation is in the same order of magnitude as the average value. For every observer, the maximum error is one order of magnitude above the average error. This shows poor modeling performance on some dynamics. For the observers from Loja do Cidadão, the result is presented for each predicted temperature individually on every metric.

TABLE XI: Performance metrics for Loja do Cidadão temperature observer

Metric	NARX Neural Network				Takagi-Sugeno			
	Heating		Cooling		Heating		Cooling	
	[^{o}C]	[%]	[^{o}C]	[%]	[^{o}C]	[%]	[^{o}C]	[%]
AAE	1.09	4.37	1.30	5.21	1.28	5.13	1.07	4.30
	1.13	4.52	1.25	4.99	1.43	5.73	1.04	4.46
ESTD	1.29	5.17	1.40	5.61	1.44	5.78	1.08	4.32
	1.41	5.65	1.53	6.12	1.67	6.68	1.12	4.46
MAE	3.15	12.60	2.03	8.13	4.28	17.13	3.08	12.33
	3.48	13.93	3.67	13.68	4.49	17.97	4.06	16.25

For the Loja do Cidadão observer, the same conclusions form the Social Security observer can be taken. The standard deviation error has the same order of magnitude as the average error and, often, an higher value. The maximum is, at least, the double of the average error for every observer. This result demonstrates a poor modeling temperature dynamics.

Every NARX Neural Network observer showed a better performance when compared to the Takagi-Sugeno for the same variable prediction.

2) Chiller Setpoint Sensibility: The sensitivity to the chiller setpoint is another important characteristic in temperature observers. To reduce the complexity of the analysis, only the sensitivity on temperature observer of Social Security store.

The followed strategy is the same as in power observers case. There is one chosen day (the same days as before) for each operating modes in which different setpoints are tested. In Figure 6, the prediction on temperature signal during one day for different constant setpoints on heating operating mode is presented.

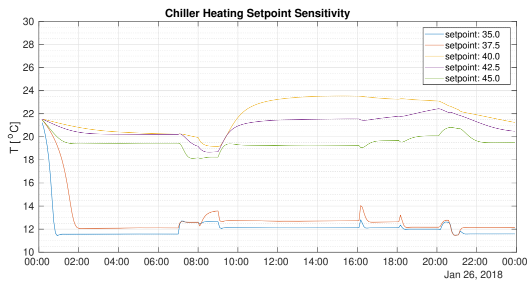

Fig. 6: Predicted temperature signals for different setpoints during an example day heating mode using NARX Neural Network

Notice that the temperature starts at the same point on every setpoint. The reason is that NARX Neural Network model strongly depends upon previous instants, which were the same for all simulation results. In Figure 6, the increasing of the setpoint does not always correspond to an increase in temperature, as it would be expected. For instance, for the setpoint of 45.0^{o}C, the temperature is always lower than for the 40.0^{o}C. This happens for setpoints which are not a part of dataset, showing that the dynamic is not well modeled for them. For the lower values of chiller setpoint (35.0 ^{o}C and 37.5^{o}C), the temperature shows an unexpected dynamic. It shows an horizontal line in every part of day except around the open and close actions on both stores and on the parts of day in which the air handlers turn ON and OFF. Though it would not be compatible with the heating operating mode.

Looking at the exterior temperature, it is easy to identify samples in which the interior temperature is lower than the exterior one for the referred setpoints. This dynamic is not compatible with the heating operating mode. The same simulation is presented for the cold operating mode on Figure 7.

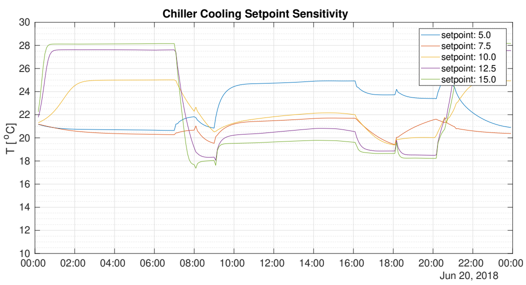

Fig. 7: Predicted temperature signals for different setpoints during an example day cooling mode using NARX Neural Network

In Figure 7, the decreasing of the setpoint does not always correspond to a decrease in temperature, as it would be expected. For instance, during a considerable part of the day, the temperature on setpoint of 5.0^{o}C is the highest value.

It makes sense for the temperature to go down during the period in which air handlers are turned ON. But is does not make physical sense to go higher than the exterior temperature, during night and with the store closed.

On both cases, it can be noticed that on setpoints which are part of the dataset, the dynamic result is much more coherent with the schedules from stores and air handlers and the outside temperature. Many of the tested setpoints are not included in the acquired data. The influence of exterior meteorological variables is not well modeled by the observers. This issue gets more evident if the considered setpoints are outside of scope of the acquired data.

For the Takagi-Sugeno model, it was applied the same method. In Figures 8, it is presented the interior temperature on National Insurance store during a day for different setpoints on heating mode.

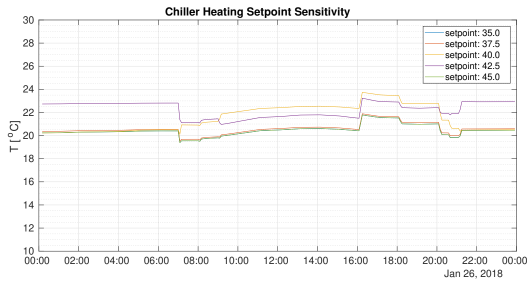

Fig. 8: Predicted temperature signals for different setpoints during an example day heating mode using Takagi-Sugeno

The results obtained on Takagi-Sugeno are similar to the ones obtained for the NARX observers when it comes to chiller setpoint sensitivity. It is not clear the effect of the setpoint on temperature. For some setpoints, the temperature overlaps, which shows that the modeling differences are small ones. An higher setpoint does not necessarily imply an higher interior temperature. At this point, there is no clear dynamic that should be directly excluded like it is on NARX observer. Despite that, an interesting result is that the setpoint does not alter the shape of the signal. The setpoint acts as an offset to the temperature signal, increasing or decreasing the same value in all samples. This result, despite being coherent, is not coherent with an highly non-linear system. In Figure 9, the interior temperature on Social Security store during a day for different setpoints on cooling mode is presented.

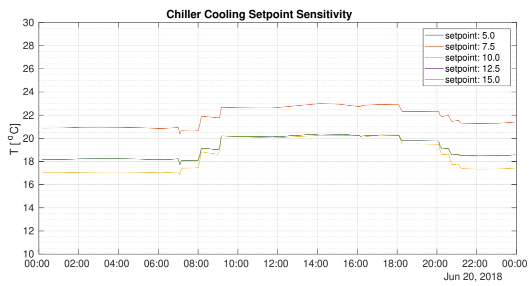

Fig. 9: Predicted temperature signals for different setpoints during an example day cooling mode using Takagi-Sugeno

On cooling mode, there is an higher number of overlapped signals than on heating mode. The same conclusions taken from the heating case can be taken here. There is no clear relation of the setpoint with the resulting temperature and changing it just adds or subtracts a signal offset.

VI. Optimization and Observers Integration

Integrating the optimization algorithms with the observers is not as trivial as it may look. Remember that every result presented on next chapters depends on performance of every module described before, but also on how the integration is done.

In every result presented, there is a definition of as optimization scenario, a set of conditions which influence the optimized chiller setpoint. It includes the operating mode and the input variables in observers which are not optimized variables. In this case, every input variables, except for the chiller setpoint.

The optimization allows choosing for the advised chiller setpoint within certain limits, different for the heating or cooling case. It is important to notice that for cooling case, it might be running 1 or 2 chillers. During the course of work, the only given access was in one of the two chillers which are part of the HVAC. On both operating modes, the setpoint changed is on the same chiller.

A. Optimization Cost Function

The cost function is the mathematical way to calculate a cost value associated with each optimization scenario. Considering it, the cost varies with the variation of the chiller setpoint.

The chiller setpoint does not directly relates with any of the objectives. Instead, it changes the dynamic of the HVAC, which influences both cost values. For this implementation, the lack of any realtime sensor makes it necessary to use a models to predict the dynamics, in order to calculate the energy cost and thermal comfort. This step executed by using the power and temperature observers.

The integration of the observers in the optimization algorithm is done through the cost function. The diagram of the cost function is presented in Figure 10.

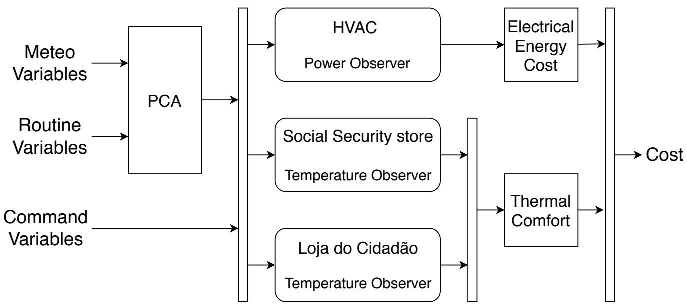

Fig. 10: Cost function diagram

The cost function is divided in three main areas of calculation. The first one for data extraction, done with PCA algorithm, the second one to predict intermediate dynamics, using mathematical models and the third one to calculate the cost, by considering these intermediate values. The PCA algorithm is applied based on the same vectors calculated during modeling.

B. Pareto Optimal

The considered method during this dissertation implementation for selecting the best point from the Pareto frontier is the *Weighting Method*, presented at [7]. It consists in choosing weight values for each objective and giving a certain intuition of the importance of each objective compared with each other. In particular, the weights chosen are 40% for the energy cost and 60% for the thermal comfort one, applied on points already obtained and belonging to the Pareto Frontier. Notice both objectives are represented in different orders of magnitude. For it to result, there is a normalization process applied before.

VII. RESULTS

The system presents an chiller setpoint based on an optimization scenario with a one week duration, starting on a Monday and ending at a Sunday. The scenarios are tested using NSGA-III and PSO meta-heuristic. However, is this article, only the NSGA-III results are presented due to their similarity. The environment conditions tested are one week from one from January of 2018 for heating operating mode and one from June of 2018 for the cooling operating mode.

For the NSGA-III meta-heuristic, the maximum iteration number is 50 with a population size of 10, randomly initialized. It is configured with crossover ratio of 0.5 and a mutation rate of 0.02. On each scenario, it is presented the graph showing the Pareto solution set, the power and the temperatures, predicted for the optimal setpoint and the real one, in which the data was acquired.

1) Heating Mode: The Figure 11 presents a cloud of 10 points, corresponding to the 10 population points. The orange points are the ones belonging to the Pareto frontier, with the green one representing the selected one and the other points are in blue.

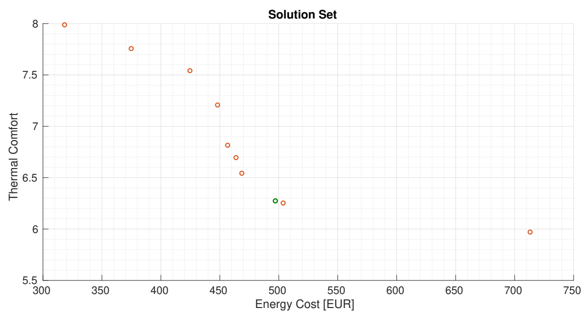

Fig. 11: Pareto set points for NSGA-III optimization on heating mode from Jan 29 to Feb 05

In the presented case, all population points converged into points present in the Pareto frontier. The setpoints are the same as before: 42^{o}C in 29th January and 39^{o}C between 31th January and 4th February. The switch happened at 17h of the 30th January. The optimal setpoint is 39^{o}C. The power used during acquisition real and the predicted one with optimal chiller setpoint is presented in Figure 12.

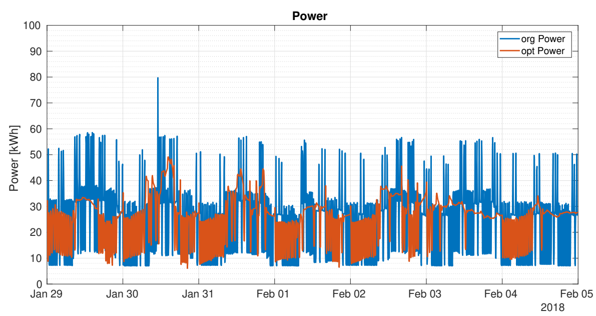

Fig. 12: HVAC power on acquired and optimized chiller setpoints

The real and optimal chiller setpoints produce similiar energy costs. The real situation costed 379.61 €. The optimized setpoint situation have a cost of 397.29 €, an increase of 3.68% in energy cost. The energy costs in the real situation and the optimized one are closer in this case. The reason is clear, a significant part of the week, the setpoint is the same for both situations. The Figure 13 shows the temperature inside the Social Security store during the same period.

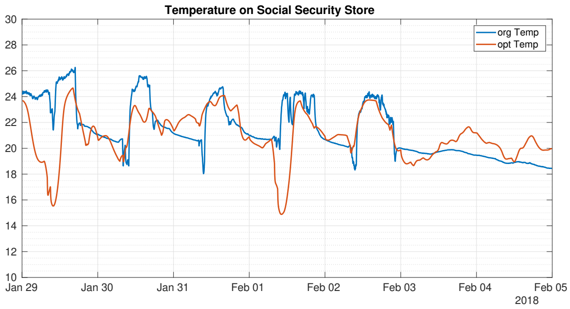

Fig. 13: Temperature signals on Social Security store for the acquired and the optimized chiller setpoints

The temperature inside Social Security store presented on Figure 13 shows a much more coherent dynamic than the previous situations presented. The duration in which the setpoint is coincident for both situations, there is not an high error in between both temperatures in terms of values (there is a dynamic difference, though). For the temperature in first days presented, there is a big decreasing around the opening of the store. This is a modeling flaw in the observer, which considers the effort on the optimized not to be enough to increase the temperature on the store opening. This is the time of the day where the most effort is required since there is too little actuation from the HVAC during night. The resulting predicting dynamic is not an expected one to happen. In Figure 14, it is presented the temperature inside Loja do Cidadão during the same period.

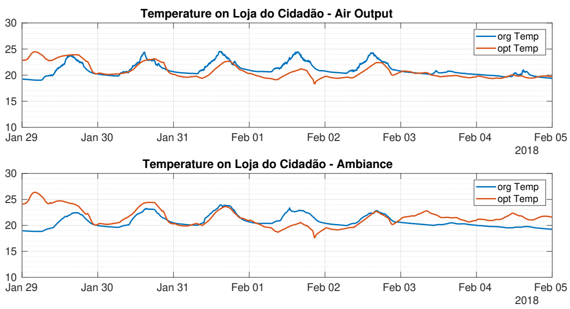

Fig. 14: Temperature signals on Loja do Cidadão store for the acquired and the optimized chiller setpoints

The temperature observer showed a better prediction results in Loja do Cidadão.

2) Cooling Mode: The Figure 15 presents a cloud of 10 points, corresponding to the 10 population points. The color code is the same as before. The orange points are the ones belonging to the Pareto frontier, with the green one representing the selected one and the other points are in blue.

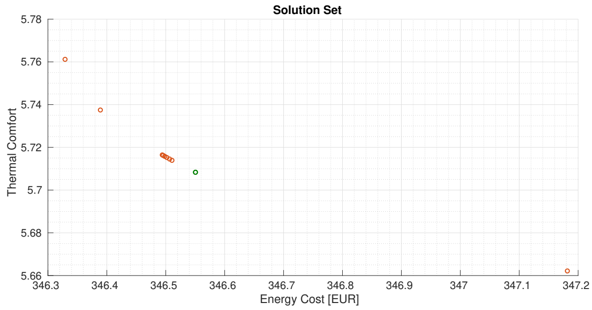

Fig. 15: Pareto set points for NSGA-III optimization on cooling mode from Jun 25 to Jul 02

The same happened as the last optimization scenario on NSGA-III algorithm, the entire population converged to the Pareto frontier. During the entire duration the setpoint was 8.5^{o}C in real situation. The setpoint which corresponds to the chosen point is 6.0^{o}C. The Figure 16 presents the power in the same scenario.

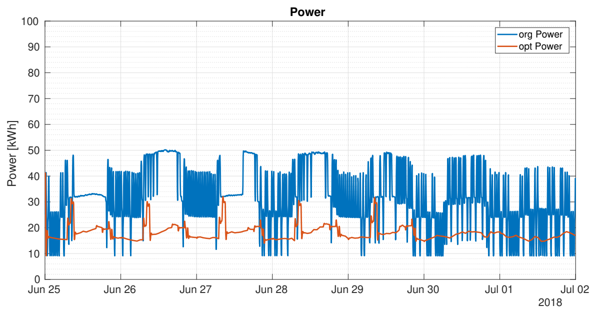

Fig. 16: HVAC power on acquired and optimized chiller setpoints

The result is expected, the setpoint is almost the same as before. The cost of 626.18 € on the real situation compares with a cost of 346.60 € in the optimized setpoint, a spare of 44.65%. The temperature inside Social Security store is presented in Figure 17.

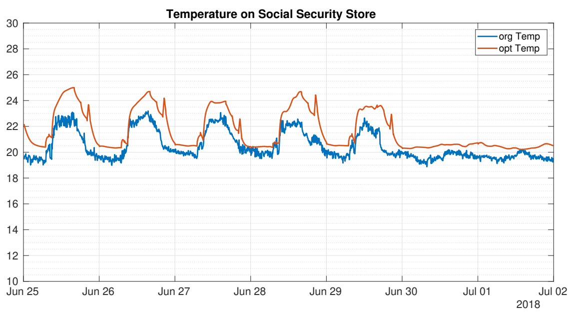

Fig. 17: Temperature signals on Social Security store for the acquired and the optimized chiller setpoints

The temperature daily evolution shows an average temperature around 23.5^{o}C during a day. Comparing this with the expected comfort temperature observed in Figure 3, it is a temperature acceptable for the range of temperatures in Summer. There is an incoherence in results caused by the observer modeling. By comparing the real situation and the one on the optimal setpoint, it seems to exist a smaller effort on the HVAC system for cooling. This result is not an expected one, notice the chiller setpoint on optimized situation is 5.8^{o}C instead of 8.5^{o}C. Figure 18 presents the temperature signals on Loja do Cidadão.

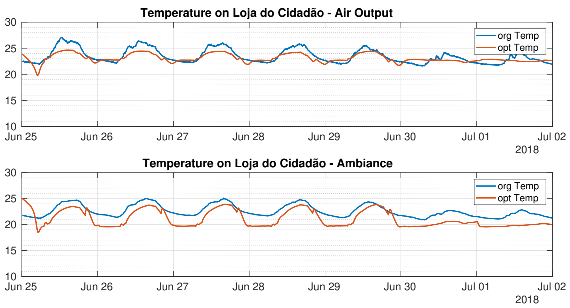

Fig. 18: Temperature signals on Loja do Cidadão store for the acquired and the optimized chiller setpoints

The temperature evolution inside Loja do Cidadão is a more coherent one for the selected chiller setpoint. While it shows a higher cooling effort by having a lower temperature in almost all samples during the day, it keeps the average temperature in near the 23^{o}C.

VIII. Conclusions

This master thesis presents a method to improve the HVAC system usage based on open-loop optimal control applied on the chiller setpoint. It presents a start to end case study applied to the HVAC from Cascais Center case study. The results obtained on this implementation are, however, not conclusive with either the success or insuccess of the methodology used. The reason is that, for an optimal optimization method to work, there is a need of ”good” models. Their performance revealed, however, not enough for the control strategy to result. The reason is that, during the data acquisition, there were constraints in logger devices availability and also in schedule availability to acquire data on Cascais Center.

This dissertation allowed the comparison on two meta-heuristic algorithms and two predictive models for the observers. On the optimization side, the results are similar for both NSGA-III and PSO. Still, there is an advantage in using NSGA-III, noticeable on number of iterations to converge. On the observers side, the NARX Neural Network showed better results than Takagi-Sugeno. It is important to notice the feature implementation differences on both, though.

There is an important consideration to be made on the optimization scenario. It is not realistic to have a short duration on a setpoint which is only manually changed. Despite that, the prediction methods improve their results as the predicted sample gets closer. In an implementation, the prediction is part of the system, but also of the data, since the meteorological data is also predicted.

On future work, the improvements should be based on improving the observers. This can be done by decoupling data acquired and modeled, simplifying their dynamics. The thermal comfort can be, also, data-driven modeled, improving its estimation. On the optimization, a more complete set of commands (instead of just the chiller setpoint).

References

[1] enerdata, https://yearbook.enerdata.net/electricity/electricity-domestic-consumption-data.html, accessed: 2018-08-07.

[2] “yarpiz,” http://yarpiz.com/category/metaheuristics, accessed: 2018-07-16.

[3] R. McDowall, *Fundamentals of HVAC Systems: SI Edition*, 1st ed. Elsevier, 2007, iSBN: 978-0-12-373998-8.

[4] “meteoblue,” www.meteoblue.com, accessed: 2018-09-07.

[5] ANSI/ASHRAE 55-2010, *ANSI/ASHRAE 55 Thermal Environmental Conditions for Human Occupancy*, 2010.

[6] K. L. Du and M. N. Swamy, *Search and optimization by metaheuristics: Techniques and algorithms inspired by nature*, 2016.

[7] J. Branke, K. Deb, K. Miettinen, and R. Slowinski, *Multiobjective Optimization: Interactive and Evolutionary Approaches*, 2008.