Smart Control System for Sustainable Swimming Pools

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Abstract. Specific research programs, legislation and funding intend to protect, conserve and enhance the EU's natural capital, transforming the EU into a green, competitive, low-carbon and resource-efficient economy. These guidelines aim at protecting European citizens from health and environmental risks. Indeed, there is an increasing interest on decarbonization of the electricity generation, with a special focus on the introduction of Renewable Energy Resources (RES).

This paper is a preliminary insight into a new control approach from where smart decision is made based on predictions returned by models of sustainable thermal systems (local renewable sources generation devices) and on information gathered from an array of sensors in order to regulate swimming pool's water temperature. The information (ambient variables and sub-systems internal transfer function modelling) is then combined with an optimization framework which goal is to ultimately, reduce the requirements for human intervention in the swimming pool maintenance and provide resources savings for the final user in terms of financial and natural resources, contributing to a sustainable environment. The research work is developed within the scope of the Ecopool+++ project: Innovative heated pools with reduced thermal losses.

Keywords: Renewable Energy, Model Predictive Control, ARMAX, Outdoor Swimming Pools.

1 Introduction

The European Union and its national governments have set clear objectives to guide European environmental policy up to 2020 and a longer-term vision (for the next 30 years). Specific research programs, legislation and funding intend to protect, conserve and enhance the European Union's (EU) natural capital, to transform it into a green, competitive, low-carbon and resource-efficient economy. These guidelines aim at protecting european citizens from pressures and risks to health and well-being related to the environment.

In this context, a significant portion of research is dedicated to exploring the usage of wind power, biomass and solar power for replacing traditional energy sources as they pose many advantages such as little environmental risk and are envisaged as a means to comply to European and global environmental norms [1].

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DOI: 10.1007/978-3-031-36030-5_44

Consulting the power consumption data supplied by Portuguese statistics portal Pordata [2], and for the case of Portugal, in the civil year 2020 it was observed a total of 15215 thousand tep (tons equivalent petrol) due to energy consumption. The figures also show that the energy sources like petrol corresponded to 6260 thousand tep, gas to 1740 thousand tep, renewable energy mix of wind, hydro and solar a total of 2905 thousand tep, and the remaining consumption was due to electrical energy.

As such, the previous figures identify Portugal as one of the European countries where the effective penetration of renewable energy (power usage) is significant (as it is responsible for 19% of the overall energy consumption) with a higher impact when compared with the average value of 11,7% in the EU. Therefore, demand for new sources of flexibility and growing recognition of the multi-energy nature of districts are increasing interest in the interaction between energy sectors, like electricity, heating/cooling, gas and in the significant amount of flexibility available from heating [2, 3].

Solar energy, a form of renewable energy not only is abundant in our environment but can reduce the harmful environmental gas emissions resulting from the burning of fossil fuels. The most common way of using solar power is to convert sunlight into heat energy to produce hot water, through the usage of solar thermal collectors. In such case, the basic mechanism uses the incident solar radiation for generating heat as it converts the irradiated energy into thermal energy. There are many different applications where solar heat energy can be used, such as domestic water-heating systems, pool-heaters, and space-heating systems [4, 5].

In this scope, this paper proposes a new scheme to increase and control a swimming pool's water temperature using sustainable thermal systems (local renewable sources generation devices). The aim of the control system is to coordinate the functioning of a set of thermal energy sources and thermal storage, to adjust the water temperature of outdoor swimming pools according with user requirements. It relies on information gathered from an array of sensors and on weather variables forecast which are then combined with an optimization framework.

The system goes way beyond traditional systems [6, 7] where typically only efficiency is addressed and the number of systems is small (solar and gas based thermal systems). Further, we address the development of methods for system identification and future time-based forecasting, using machine learning methods, and employ optimization based in simulated data, to control the water temperature in the swimming pool's tank. The control of the water temperature is set according to a setpoint as specified by the user. The idea employed explores the ability of the control system to make a proper decision on the required control signal.

The remainder of this work has the following structure. We start by addressing other works related to this work in Section 2. Next, a description on the problem is made in section 3. Section 4 specifies the mathematical formulation of the problem. Section 5 presents the results of the three scenarios considered. Finally, section 5 draws results and presents perspectives on future work.

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DOI: 10.1007/978-3-031-36030-5_44

2 State of the Art

The work in [8] proposes a new scheme for monitoring and controlling the swimming pool's quality (pH, chlorine, water level, temperature, water pressure) through a low-cost system based on wireless sensor networks. Despite having economic benefits by consuming less natural and material resources, it does not consider thermal comfort and does not include sustainable thermal systems.

In a similar manner, a web-based swimming pool information system was presented by Marais et al. [9]. Numerous elements of pool maintenance, for instance pH, chlorine levels and water level can be remotely monitored and further configured according to user-defined schedule.

One of the most popular heating technologies for outdoor swimming pools which is also environment friendly is based on PCM (Phase Change Material) storage tanks. In [10], Y Li and G Huang discussed their application to outdoor swimming pools and showed that they can bring out economic benefits by simply shifting electricity consumption from on-peak to off-peak periods. The water temperature regulation is made by ON-OFF control of a pump using a model of the swimming pool where the assumption that the temperature of the pool water was equal to the outlet temperature of the pool. The numerical analysis and simulations were performed within a platform that combined Matlab and TRNSYS.

In a more recent work [11], Y Li and G Huang show that performance of the PCM storage tank can further be improved by proposing a new approach where thermal comfort is regarded instead of using the outlet water temperature in the pool. As such, they have incorporated solar irradiation recorders, data logger, ultrasonic anemometer, temperature sensors, and other sensors to collect field data.

Other authors [6], analyzed the energy efficiency using a combined hot water system composed of solar thermal collectors and natural gas thermal power plant. They conclude that thermal energy sources using natural gas and solar energy remain the best solutions in terms of energy efficiency, low pollution and operating costs.

In [12], the authors use predictive control to show that indoor swimming pools water temperature's regulation can become more energy efficient when a hybridized solar + boiler system (possibly powered by biomass) is used as a thermal supply. Their results indicate that regulation based on predictive control can maintain pool thermal conditions while reducing energy demand. Moreover, they also show that this approach consumes less fuel when compared to traditional Proportional Integral Derivative (PID) control. This system is yet to be applied to outdoor swimming pools.

In [13], Dong et al, propose an integrated control system composed of a fuzzy automatic optimization algorithm and the Smith predictor compensator to adjust the temperature of pool water. The simulations show it can achieve good control effects for serious delay and serious inertia pool temperature control system.

With our proposal, the system not only is able to use more than the usual renewable systems but it also has the ability to address future time-based forecasting in conjunction with machine learning methods.

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3 Problem formulation

Typically, a dynamical system is affected by external stimuli. On one hand, there are the *inputs*, which are commonly associated with the external signals and can be manipulated by the observer. There are also *Disturbances*, which correspond to signals which can or cannot be measured. Of interest to the observer there are also the outputs. Fig. 1 illustrates the relations between the *inputs*, disturbances and *outputs* of a typical dynamical system.

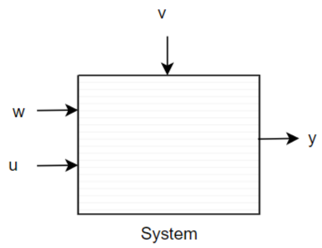

Fig. 1. System with output *y*, input(s) *u*, measured disturbance *w* and unmeasured disturbance *v* (adapted from [14]).

Generally speaking, a dynamical system is one that the future output value is related to the past inputs and disturbances according to some nonlinear function $f(y,u)$:

$$y(t) = f(\mathrm{y(t-1), y(t-2), \dots y(t-n), u(t-1), u(t-2), \dots} \\ \dots \mathrm{u(t-m)}, w, v) \quad (1)$$

Where *n* refers to the time instants or lags into the past for the output signal *y* and *m* the time instants into the past for the control signal *u*.
In its simplest description, the system considered in this work (see Fig. 2) is composed of several thermal sub-systems, which include: (1) the water tank (POOL), (2) Phase Change Material (PCM) accumulator, (3) solar collectors (flat-plate type SC), (4) Terrace Heat Exchanger (PC), and (5) Geothermal accumulator (PCGeo).

The various thermal sub-systems are connected by one or several ducts (one or more *inputs*), and monitoring valves which under activation promote water flow at a constant rate and preestablished direction regarding the retention valves setup. The complexity of the system is high because weather variables (seen as disturbances) condition the system response. Inclusion of weather variables as *inputs* is recommended as long as they can in some way be foreseen or predicted. In this work these data samples are considered available through WebApi requests to an online weather data server.

Due to multitude of sub-systems, several scenarios of operation (or *setups*) can be considered during the system operation. For example, to make water circulate through the solar collectors and the Pool, requires the operation of pump B_1 and the opening of valves V_2 and V_9. Another scenario includes water circulation from the solar collector into the duct system of the PCGeo sub-system.

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Ultimately, the goal is to regulate the water temperature at the Pool. Readings the sensors T_i (i=$1 \ldots 12$) they allow the monitoring of the temperature in each of the subsystems and provide additional information to allow the control mechanism to decide which setup is the most effective at a given moment.

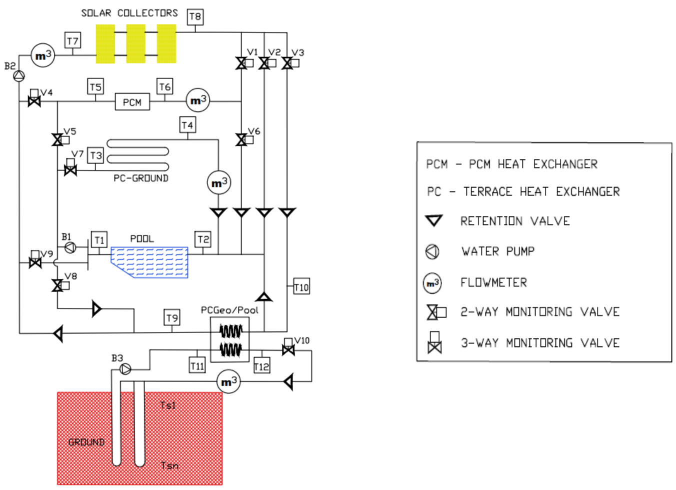

Fig. 2. Model of the Swimming Pool's water heating system using Renewable energy sources

4 Systems identification

System identification concerns finding the appropriate model for a "real" system. This includes finding the appropriate inputs and estimating the appropriate parameters values for the model. When seen as a black-box, the utilization of the model becomes simple and provides alternative control techniques in order to identify the best control signal to apply at the input of the system.

Systems identification can be performed through the analysis of time-series records for each of the scenarios or setups previously mentioned. Appropriate algorithms help define a ARMA (Auto-Regressive-Moving-Average), ARIMA (Auto-Regressive-Integrated - Moving-Average), or SARIMA (Seasonal ARIMA with exogenous inputs) models.

The choice of an autoregressive model depends on the compromise between the simplicity of the model and the properties of a time series. If a time series is said to be stationary (i.e., if its properties are not affected by a change in the time source) the models chosen are normally the Autoregressive with Exogenous Input (ARX) and/or the Autoregressive Moving Average with Exogenous Input (ARMAX). ARMAX is more complex than ARX due to the fact that it has the ability to deal with stationary time series whose error regression is a linear combination. If a time series is non-stationary, the Autoregressive Integrated Moving Average with exogenous input

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(ARIMAX) and/or the Seasonal Autoregressive Integrated Moving Average with exogenous input (SARIMAX) model can and should be used. Both models, ARIMAX and SARIMAX, are capable of handling both stationary and non-stationary series. However, if the time series has seasonal elements, the best option would be SARIMAX.

In [15], an analysis was made to forecast load demand in the context of smart grids, using ARX, Artificial Neural Networks (ANN) and Artificial Neural Networks optimized by Genetic Algorithm (ANN-GA). In this same analysis, the ARX presented a higher mean absolute percentage error but lower execution time but when compared to the ANN and ANN-GA solutions.

In [16], a hybrid model was developed to predict electricity demand as a function of outdoor temperature. It then was compared with the ARMAX model. Despite the good performance of both, and having the ARMAX presented higher forecast errors, it is simpler to define than the hybrid model.

In the current work, it was found that the modelling the system using ARMAX produced acceptable results. To this end, next we will describe the equations that define the ARMAX models.

ARMAX

Like ARX [16], Autoregressive Moving Average with Exogenous Input (ARMAX) includes additionally the moving average component. ARMAX modelling is, again, applied when a time series has regression characteristics, and the error is a linear combination [17]. The ARMAX model is ruled by the following equations:

$$\boldsymbol{\phi}(L)y(t) = \sum_{i=1}^{n} \boldsymbol{\beta}_i(L)\boldsymbol{u}_i(t) + \boldsymbol{\psi}(L)e(t) \tag{2}$$

with

$$\boldsymbol{\phi}(L) = 1 + \phi_1 L^{-1} + \cdots + \phi_p L^{-p} \tag{3}$$

$$\boldsymbol{\beta}_i(L) = \beta_{i1} + \beta_{i2} L^{-1} + \cdots + \beta_{ip} L^{-p+1} \tag{4}$$

$$\boldsymbol{\psi}(L) = 1 + \psi_1 L^{-1} + \cdots + \psi_q L^{-q} \tag{5}$$

where

- $\boldsymbol{\psi}(L)$ is the *moving average* component;
- q is the order for the *moving average* component;

and,

$$\boldsymbol{\phi}_t = [\phi_1, \phi_2, \dots, \phi_p],^T \tag{6}$$

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$$\boldsymbol{y}_t = [y(t-1), y(t-2), \dots, y(t-p)], \tag{7}$$

$$\boldsymbol{\beta}_{\mathrm{t}} = [\beta_{11}, \beta_{12}, \dots, \beta_{1p}, \beta_{21}, \beta_{22}, \dots, \beta_{2p}, \beta_{\mathrm{n}1}, \beta_{\mathrm{n}2}, \dots, \beta_{\mathrm{np}}],^T \tag{8}$$

$$[u_{11}(t), u_{12}(t-1), \dots, u_{1p}(t-p+1), u_{21}(t), u_{22}(t-1), \dots$$
$$\dots, u_{2p}(t-p+1), u_{n1}(t), u_{n2}(t-1), \dots, u_{np}(t-p+1)] \tag{9}$$

$$\boldsymbol{\psi} = [1, \psi_1, \psi_2, \dots, \psi_q], \tag{10}$$

$$\boldsymbol{e}_t = [e(t), e(t-1), e(t-2), \dots, e(t-q)]. \tag{11}$$

The coefficients of the $\boldsymbol{\phi}$, $\boldsymbol{\beta}$ and $\boldsymbol{\psi}$ polynomials are defined by equations 9-11, and estimated using the CSS-MLE method [18].

4.1 Modelling the system

One reason for using a SMart system is to provide a forecast into a specified time step into the future depending on the actuation of the thermal system in action. Here, we assume that the variables influencing the model parameters are known (predictable and available) for the prediction horizon of the controlling scheme.

As the system is based on simulation, the TRNSYS 18.0 [19] simulation tool is applied for developing the mathematical models for the sub-systems that comprise the global system.

Since at a later stage every sub-system will be employed at a local testbed, the modelling approach requires using sampled data to perform model identification. In this sense, the simulated data is retrieved from the TRNSYS tool using a specified sampling period.

The model identification procedure carried on this work is given by algorithm 1. Its goal is to find an ARMAX model for each one of the sub-thermal systems.

Algorithm 1: System modelling

Input: *a matrix of the past sampled data for the n_inp input (includes three weather variables, wind velocity, ambient temperature, relative humidity and Pool input water temperature) and the one output sampled data, size of the training data (Train_size), size of the testing data (Test_size)*
Output: *the best representation of the system according to its forecasting performance on forecasting the testing data (Best_model)*

Generate a set of M ARMAX models with randomly chosen polynomials order
For each ARMAX model
  Estimate the polynomial parameters using the Maximum-LikeLihood-Estimator (MLE)
  Calculate the Sum-of-Squared-Error (SSE) and R^2 on the training data.
  Calculate the prediction values over the testing data
  Calculate SSE value for the predicted values (SSE_predict)
Best_model = the model with the lowest SSE_predict
return Best_model

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Model Predictive Control.

The typical control approach to swimming pool water temperature regulation is based on classic control methodologies where heat exchangers such as pumps or boilers are either switched ON or OFF.

In scenarios where the right conditions are met, the application of predictive control makes it possible to anticipate the control action in advance, regarding the correct identification of the system and, consequently, the model's ability to predict the system's operation for future instants. Typically, the methodology employed uses the concept of optimization for deciding on the effective control input value (u) to be applied to the system (see Fig. 3).

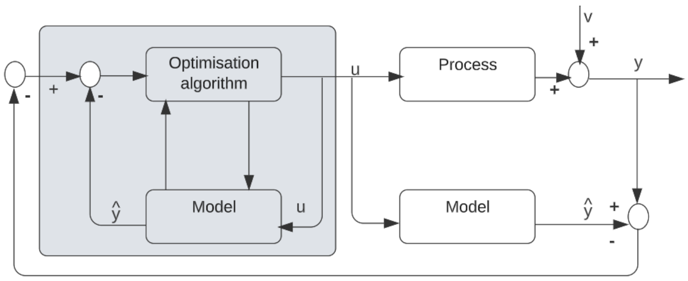

Fig. 3. Flow diagram for Model Predictive Control.

As shown in Fig. 4, using the past N_e sampled data an estimation of the best model is carried out. The model is then used to provide a sequence of control signals to the system for the prediction horizon, or *Np* future steps.

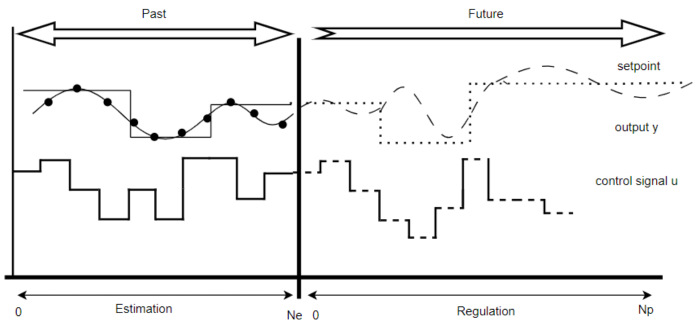

Fig. 4. System response based on generalized model predictive control.

Using an optimizer (based on a Genetic Algorithm) an optimal solution can be found, evaluating solutions that best satisfy the restrictions imposed and, in the end, selecting the best one. The optimizer considers as objective the minimization of equation 12:

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$$\begin{cases} \sum_{i=1}^{Np} \left(setpoint - \mathrm{y}_i(u_i)\right)^2 \\ st \quad \lfloor u \rfloor \leq u_i \leq \lceil u \rceil, u \in \Re \end{cases} \tag{12}$$

where *u* translates the control signal, and *y* the output of the model, as shown in Fig. 1.

Under the aforementioned conditions, the control strategy to adopt must consider modelling each of the sub-systems that constitute the overall system, for each and every control scenario.

It follows that the renewable sources integrated in the system do not allow the immediate availability of the required control signals so an alternative approach must be adopted. So, from the standpoint of optimal control the system poses a drawback: not only each of the sub-systems have serious inertia (i.e., slow *input-output* responses), i.e. they cannot provide the required inlet water temperature in the Pool immediately (water flow regulation is possible but water temperature regulation is not) because they are highly dependent on weather conditions.

One of the most common approaches for water heating in swimming pools [6] uses a gas boiler. This type of action can be classified as Assured Effort. The boiler's output water temperature (Bout) is regulated and considered to be attainable instantly (within a pre-defined duration control step). This scenario is depicted by Fig. 5, left.

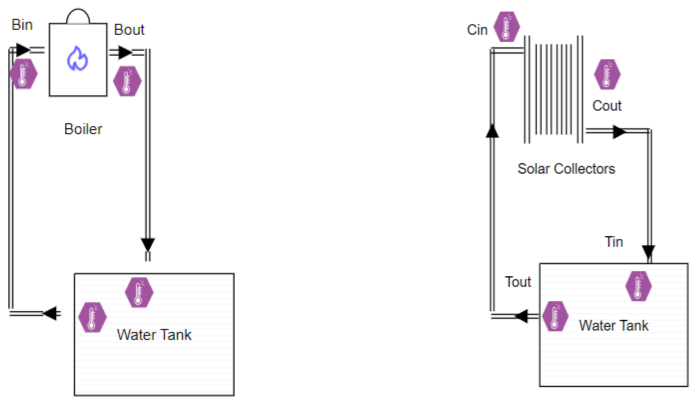

Fig. 5. The scenario considered for regulating the water temperature. Left: the boiler is used as the heating element. Right: a solar collector is used as heating element.

The type of service supported by the boiler is compared with the one supported by a solar collector of 50m^2, represented in Fig. 5 right. The type of service provided by it could be considered as Best Effort, as it will not assure that the target temperature could be met, since it depends on weather conditions that are not controllable.

The core of the control system is based in an Energy Management System (EMS), with a Model Predictive Controller, which is responsible for finding the optimal value for the pool inlet water temperature (control signal) and according with the predicted

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values on the weather variables. In this sense, the system accounts for user preferences as it estimates the required set of water temperatures of the output of the boiler that will drive the swimming pool's water temperature to the desired setpoint. This scenario is accomplished with the help of an optimizer, using the Genetic Algorithm (GA).

In the following sub-section the genetic algorithm basics principles are explained.

4.2 The genetic algorithm for controlling the boiler system

The Genetic Algorithm was used to find the most appropriate set of future water temperatures for the boiler output, in a pre-defined prediction horizon. The fitness of the candidates was computed according with Eq. 12.

In this case, the encoding of the chromosome in the genetic algorithm consists of a list of real-valued genes where the i_{th} position element encodes the expected temperature value of the boiler output at the i_{th} future time step, for a pre-defined range of possible values. For instance, for a prediction horizon of 4 steps, and possible values in the range [4.0, 33.0], the i_{th} individual chromosome could be translated by:

4.0	15.0	23.4	33.0

As crossover a uniform operator using single point was used. Mutation probability was based on a gaussian distribution. In summary, the default crossover and mutation operators were used. The termination criteria was the number of generations.

5 Simulation tests and results

To execute the simulations, sampled data (with a sampling period of 30 minutes) was obtained from the TRNSYS numerical simulation of the swimming pool. It was then divided into the training and testing parts. Weather records such as ambient temperature, wind speed and relative humidity were also collected and added to the training data.

The training data used a set of past values. In the following, N translates a parameter that indicates the number of past time steps used to define the training data. Initially different values of N were used to compare the variations of the model. The best value was then set constant. The testing data includes sampled values for the future time steps according to the prediction horizon considered, and considered being available at present time.

The performance of the models were evaluated using several metrics. The metrics were the Sum-of-Squared Errors (SSE), and Mean Relative Error percentage (MRE%). The first metric was also used by the search algorithms during model estimation, while the second metric is a key figure for comparing performance between solutions.

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5.1 Results with the ARMAX model

As it was pointed out before, the weather variables were used as exogenous inputs to the ARMAX model, and so, was the water temperature at the output of the collector (Cout in the right image of Fig. 5).

The period of the year used for testing was in the month of April (specifically in the second half of April) when the weather conditions traditionally are not adequate to raise the pool's water temperature above 20ºC without introducing complementary equipment. Fig. 6 represents the water temperature of the swimming pool, without solar collector versus using a solar collector.

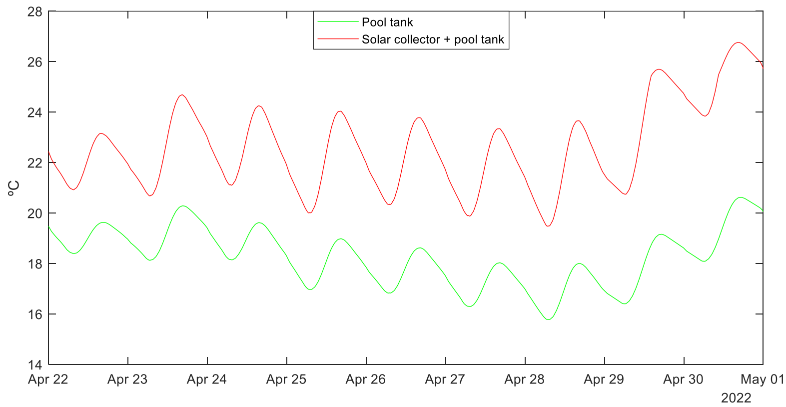

Fig. 6. Comparison of the water temperature of the swimming pool, without solar collector versus using a solar collector, between the 22nd and the 1st of May.

Data measures (from the TRNSYS simulation) before 8h of April the 28th, were used as training data. The following interval of 12 hours was used as testing data (which correspond to 24 time steps of 30 minutes), i.e., predicting the system output from 8h till 20h on that day.

Table 1 shows the metrics obtained from a list of ARMAX models retrieved using the procedure described by algorithm 1 (section 4.1) where M=10, for several sizes of training data sets. As it can be observed the size of the training data plays a decisive role in the model's ability to give adequate predictions in the horizon considered. This trend is observed not only for the SSE value for the training data, but also for the SSE value on the testing data. It follows that the value for SSE is size dependent which is not the case for the MSE.

The best model is the one which presents a SSE value for the testing data of 9.86×10^{-2} which used a total training data set of N=320. The prediction for 24 steps into the future (in steps of 30 minutes) is given in Fig. 7.

Then, to assess whether this model (the one with lowest SSE for testing data) is also capable of achieving accurate predictions, the model was used to make predictions for 24 future time steps beginning at other specific hours, according to Table 2. The results show that the MRE prediction error ranges from 0.086 % to 0.24 %.

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Table 1. Models performance metrics for different training data sizes

	Polynomial orders {ϕ, β_i, ψ}	**SSE (training data)**	**SSE (testing data)**	**MRE % (testing data)**	**MSE**
80	{5, [4 2 2 5],1}	5.97	5.98	1.96	1.23×10^{-4}
80	{10, [8 6 4 2],7}	7.45×10^{-1}	1.26	8.62×10^{-1}	6.41×10^{-5}
160	{9, [10 1 6 1],9}	1.19×10^{-1}	9.52×10^{-1}	8.03×10^{-1}	1.22×10^{-4}
160	{8 [2 9 10 6],9}	6.0×10^{-2}	1.48	9.06×10^{-1}	9.40×10^{-5}
320	**{6, [5 9 3 5],10}**	$\mathbf{1.72\times10^{-1}}$	$\mathbf{9.86\times10^{-2}}$	$\mathbf{2.44\times10^{-1}}$	$\mathbf{1.18\times10^{-5}}$
320	{5, [7 1 9 6],9}	1.86×10^{-2}	3.26×10^{-1}	4.11×10^{-1}	1.26×10^{-5}
1920	{5, [2 4 10 6],10}	2.82×10^{-2}	1.03	7.94×10^{-1}	2.38×10^{-4}
1920	{7, [8 5 7 2],10}	2.26×10^{-1}	9.14×10^{-1}	7.34×10^{-1}	2.41×10^{-4}

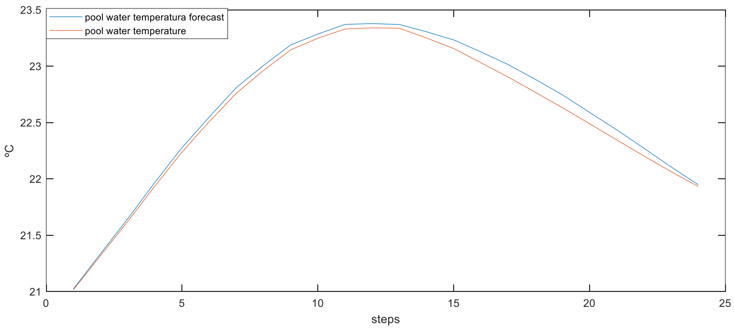

Fig. 7. ARMAX Pool Water temperature 24 steps forecast

Table 2. The best model SSE metric when used to predict 24 steps into the future, beginning at 8h, 12h, 15h and 19h into the 28th of April

Starting hours	**MRE%**
8h (day and hour used for finding the model)	2.4×10^{-1}
12h	8.6×10^{-2}
15h	1.2×10^{-1}
19h	6.4×10^{-2}

The three scenarios were then compared on April the 28th. In general, the system needs to decide at a given time instant, if it fully relies in the forecasted generation given by the solar collectors, or if it requires using the gas heater. In particular, and based on the difference between the highest predicted pool water temperature and the target setpoint, the system was made to decide that at 8h it needed to regulate the water temperature at the boiler output to achieve the target temperature of 25º C. To this aim it runs the

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genetic algorithm, and together with the model's predictions combined with the forecast weather data it estimates the required water temperature at the boiler output (Bout) minimizing equation 12, as discussed in section 4.1 (case of assured effort).

Fig. 8 shows how the three scenarios compare for a temperature setpoint of 25ºC for that particular day. A closer response to the setpoint temperature is expected in the assured effort case, as this is driven by the usage of the genetic algorithm capacity to find a suitable sequence of the boiler's output water temperature. Nevertheless, if sustainability is a priority, the best effort guarantees a good profile for the water temperature, although not always reaching the desired temperature, in these specific weather conditions.

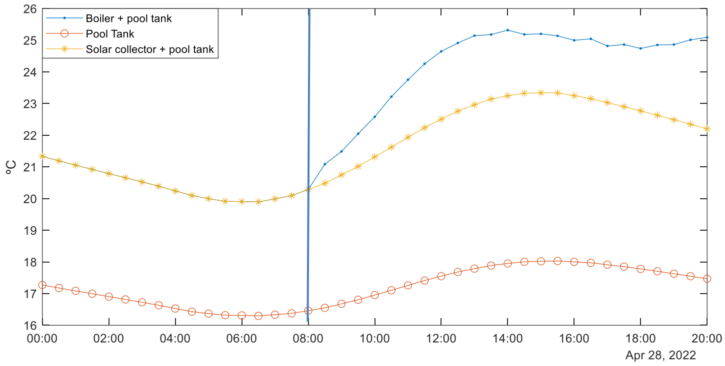

Fig. 8. Comparison between control based on assured effort (Boiler) with a MRE% value of 11.38%, best effort (Collector water temperature) with a MRE% value of 16.05% and no control (Pool water temperature) with a MRE% value of 45.65%.

The estimated temperature values of Bout (the required control signal of the system as illustrated in Fig. 4) defined by the GA optimizer for the 12 hours prediction horizon (24 steps, starting at 8h) are given in Fig 9.

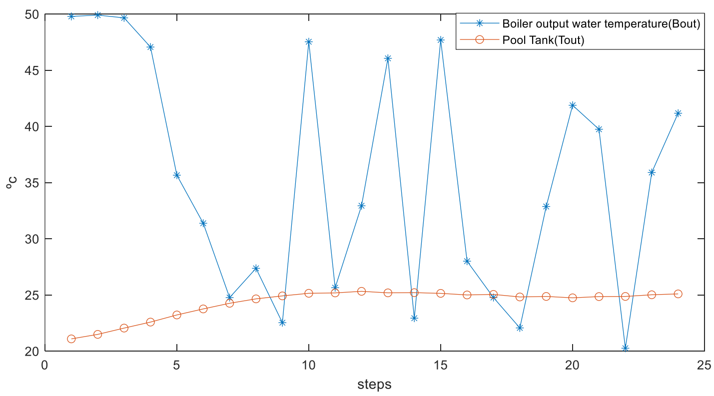

Fig. 8. Comparison between: (*) the estimated values of boiler output water temperature as a result of applying control based on assured effort and (o) the solar collectors output water temperature as a result of best effort.

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DOI: 10.1007/978-3-031-36030-5_44

6 Conclusions

This paper gives insight into a new scheme for setting up the swimming pool's water temperature through the usage of sustainable thermal systems (local renewable sources generation devices). Because of the complexity of the system, a list of several setups are considered beforehand and their application over time is set automatically according to their performance at a particular time range.

A simple setup case is explored where only the solar collectors are applied to control the pool's water temperature. The performance of this control system was compared to a setup where, traditionally, heating systems such as boiler are applied.

The results have shown that not always is the system able to satisfy the specifications set by the user but the inclusion of the renewable based system (solar collector) can make the system more eco-sustainable while ensuring the desired water temperature under very specific environmental conditions. When the user preferences become very strict the usage of the boiler can lead to an acceptable water temperature in the Pool.

This approach of control based on scenarios and having the system a degree of autonomy, requires lower human intervention in the swimming pool maintenance is gradually attained.

Future work will address the application of the SMART control approach where the selection of the setup scenario will be automatically defined within a pre-defined prediction horizon. In that case the model forecast ability here addressed will be prominent for defining which of the setups will be prioritized ahead as to guarantee that the best combination of setups will be applied.

It is the authors conviction that incorporating this methodology will provide resources savings for the final user in terms of financial and natural resources, contributing to a sustainable environment.

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DOI: 10.1007/978-3-031-36030-5_44