VALUE OF BUILDING SIMULATION IN SPORT FACILITIES OPERATION

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ABSTRACT

This paper presents a novel methodology that aims at optimising energy flows and HVAC control in Sport and Recreation Buildings. The proposed methodology integrates the use of building simulation and artificial neural networks to support better operation of Sport facilities, which are unique in terms of variable energy demand profiles and complex environmental conditions. The overall methodology is presented in conjunction with a demonstration case study. A procedure for swimming pool simulation is also tested within the case study work.

INTRODUCTION

Buildings consume 40% of Europe's total energy consumption (EUROSTAT 2008), about 8% of this energy is consumed by sport facilities (Basañez-Unanue & et al. 2008). Sport facilities are a specific building type that possesses unique features such as:

- variable energy demand profiles (timing and peaks) and usage patterns (long periods of low use and then short periods of high use sporting event);
- complex environmental conditions (comfort and ventilation requirements);
- facility functional characteristics (e.g. swimming pools, indoor courts, saunas, and the like) and open spaces (multiple buildings, complexes, parking areas, lighting, etc.).

With the Energy Performance Building Directive (EPBD) (European Union 2002), Europe has introduced a methodology to assess building energy consumption as a static measure (e.g. the energy consumption of the building independent of the behaviours of the inhabitants or operational factors). However, building operation performance, especially in sport facilities, significantly depends on the dynamic behaviour of building occupants, internal and external environmental conditions and the energy systems servicing these buildings. Building/System operation strategy is normally decided at design stage according to standard practice and not building specific values and schedules. Building operation strategies are seldom modified to account for the dynamic nature of building operation. Moreover, Heating Ventilation and Air Conditioning (HVAC) system performance degrades over time and requires maintenance, continuous adjustments and tuning of the control parameters. Building Management Systems (BMS) are used primarily for automated control purposes and typically operate on the basis of schedules and set points specified at design and implemented at commissioning. Although BMS provide the functionality to manually adjust schedules and set points during building operation, this is not common practice (Costa et al. 2009).

Underpinned by advances in technology, the EPBD recast (which recommends intelligent metering solutions), and a decrease in installation costs (Jang et al. 2008), sensors, sub-metering, and smart metering strategies are being championed as potential new technology strategies and technology solutions . Although these strategies are providing building managers with increased information about their facilities, there is still a lack of knowledge and adequate tools to support the facility manager in making the best energy management decisions by manually or automatically changing building operation strategies according to dynamic building usage or testing the effects of different operation strategies on building/system performance (IEA 2005). In sport facilities, it is expected that dynamic adjustment of the operational behaviour of HVAC systems would result in significant energy savings (Messervey & et al. 2011).

Artificial Neural Networks (ANN) have been applied to energy systems in order to improve control and performances (Kalogirou 2001), (Sterling Garay & Sanz Garcia 2010), however they have not yet been widely included in commercial products. Published studies (Artuso & Santiangeli 2008), (Trianti-Stourna et al. 1998), focus on energy solutions for sport facilities utilising energy simulation, however they do not address simulation assisted building and system operation.

SportE^2 is an ongoing European research project (SportE2 2010), which aims at managing and optimising energy flows in Sport and Recreation Buildings. SportE^2 promotes the development of a new scalable and modular technology based on four different modules: smart metering (SportE^2 How), integrated control (SportE^2 When), optimal decision making (SportE^2 Why), and multi-facility management (SportE^2 Where). This paper focuses mostly on the "Why" module which has the premise that given smart metering data and the ability to control facility energy flows, it is then possible to determine and execute optimal energy management decisions. Over time, and as data is collected, the SportE^2 Why Module will learn how a facility is operating, why current practices are not optimal, and what control actions will lead to energy savings, focusing on energy prices, weather forecasting, and the planned facility usage. To achieve this goal, SportE^2 Why will integrate both energy simulation tools and ANN in a commercial product targeted for sport facilities.

This paper presents the initial work on the SportE^2 Why Module in investigating how energy simulation and ANNs can support an enhanced operation of sport facilities with a particular focus on their energy and comfort performance. An novel study incorporating a swimming pool model in EnergyPlus and a coupled artificial neural network is also presented as an early stage demonstration of the proposed methodology.

PROPOSED METHODOLOGY

Overview

The proposed methodology develops, tests and implements optimal operation strategies in sport facilities using energy simulation and artificial neural networks. The initial test of possible optimisation scenarios is carried out in "physical" energy simulation models (e.g. EnergyPlus or others) in order to identify the energy/comfort impact of the suggested changes in the operational strategies. These simulation models provide a better understating of the problem and of the relationship between the different parameters involved in the simulation. The high resolution data set generated by the physical models is then used to train Artificial Neural Networks that are then used for optimisation purposes. The goal is to optimise customised HVAC systems operation, depending on expect occupancy and weather conditions focusing in particular on two different types of optimisation:

- Optimisation of indoor environmental schedules (mainly air temperature, and possibly air RH, pool water temperature depending on available controllers);
- Optimisation of HVAC control (e.g. air flow rate of the Air Handling Unit and water flow rate and/or water temperature in the AHU coils).

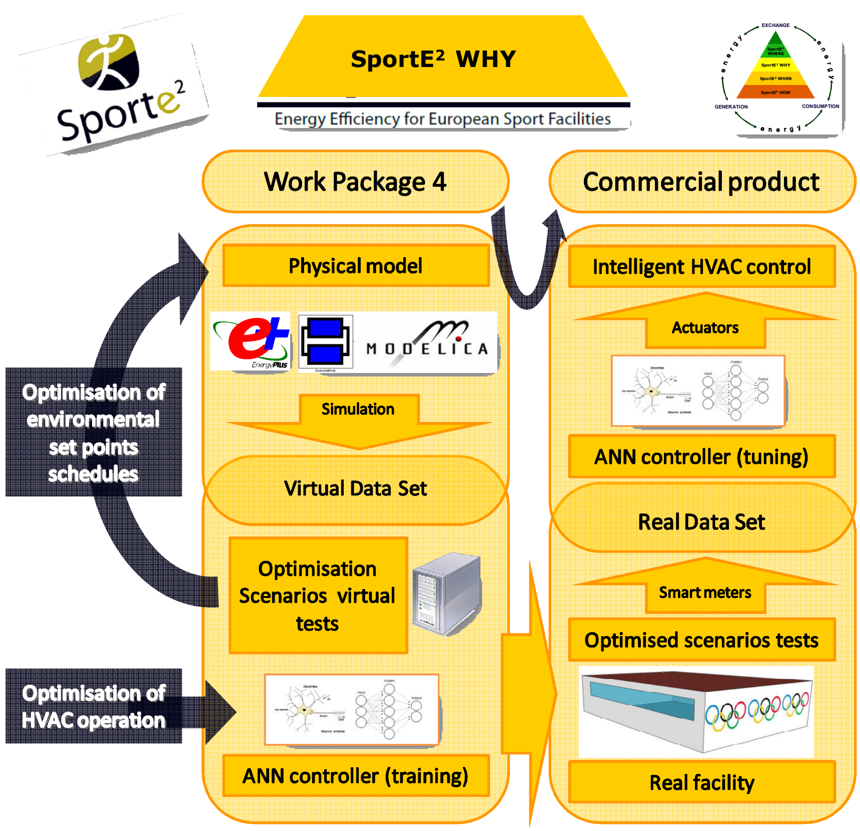

Figure 1 - SportE^2 WHY methodology

Energy consumption and comfort conditions during occupied hours is measured and considered for the optimisation of the indoor environmental schedules. Whereas for the optimisation of the HVAC control, the objective function will depend on variation between set points and actual values of the controlled environmental variables (e.g. avoid unnecessary heating/cooling and overshoots of the air temperature in conditioned spaces).

The proposed methodology) incorporates the use of building energy simulation (physical model) to estimate the impact of different operation strategies on both energy consumption and user comfort, in order to optimise indoor environmental set point schedules. The operation strategies are defined by optimisation scenarios and tested in the model environment. The test activities facilitate the standardisation of such tests for subsequent use in the real facility (e.g. test of the response time of the indoor temperature for given outdoor air temperature, solar radiation, zone occupancy and system operation, etc.).

The datasets generated during the optimisation tests are also used to train ANN based controllers, which are used in the optimisation of the HVAC system operation. In the first phase the controller is trained by the virtual data set from the physical model. In the second phase the ANN based controller is tuned with a real data set measured in the facility. Once the ANN controller is trained and tuned it can be used for optimal HVAC operation and connected directly to the actuator for online control in the real system.

The next sections describe in greater detail the main components of the proposed methodology: physical model, optimisation scenarios and ANN based controller.

A **physical** Building Energy Simulation (BES) **model** allows the virtual simulation of building and HVAC system behaviour in given internal and external conditions. A whole building energy simulation tool is used to model the energy flows in a building. Modelling the performance of a building and its HVAC system allows a better understanding and optimisation of the building and system design and operation. Several simulation tools, such as EnergyPlus, TRNSYS and ESP-r are available for this purpose and include many innovative simulation capabilities. However, the main issue with today's building simulation programs is that they do not address R&D needs in respect of HVAC systems operation because they oversimplify controls: HVAC models are quasi steady-state and "Control" is based on "requested energy" not on actual feedback control (Wetter & Haves 2008). In order to overcome the control issue in this work, after an initial adoption of EnergyPlus for modelling the building and the HVAC system, it is intended to use the Lawrence Berkeley Laboratory (LBL) Building Control Virtual Test Bed (BCVTB) to couple EnergyPlus for the building model to the LBL open-source building library which includes component models for HVAC and control systems (LBL 2011). This library is based on Modelica, an equation-based object oriented language. The library is currently developed to support computational science and engineering for innovative building energy and control systems. Also the integration with Matlab-Simulink (available within the BCVTB) will be considered for control purposes.

Another issue with whole building energy simulation models is that they require high computational power and therefore, when many simulations are required for optimisation purposes, the simulation time becomes a constraint. In order to address this problem the proposed methodology intends to utilise ANN models to learn and replicate the physical models as described in the next section.

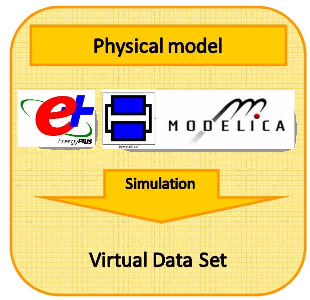

Figure 2 - Physical model overview

Initial **optimisation scenarios** are used to understand the building behaviour under different conditions and indentify parameters and schedules that can be optimised. This process leads to a definition of tests that will be carried out at the facility in order to identify facility specific characteristics of the considered variables and facilitate the tuning process of the ANN based controller. Two example of optimisation scenarios are:

- to understand the energy and comfort impact of changes in set point schedules (e.g. air temperature);
- to identify the response time of the system to the inputs considered (e.g. occupancy, outdoor air temperature and solar radiation).

The proposed **ANN based controller** consists of an ANN model agent and an optimisation algorithm. The ANN model agent is trained to replicate and substitute the physical model and will be used to predict future behaviours of the environmental conditions in the zone due to the application of different control strategies. The optimization algorithm uses the results from the ANN model agent to calculate, within a certain future time horizon, the optimal control signal to be applied to the system.

An ANN model is preferred over a physical model, because after training has been made, the neural networks can simulate the same physical model without the necessity of solving complex differential equations but instead performing simpler arithmetic calculations thus improving computational cost of the model and the time required to compute any result. Nevertheless, a physical model or a real dataset is needed for off-line training purposes of the ANN model at the early stage of the modelling process. For training purposes the choice is between the real dataset and the physical model. The latter is preferred due to the possibility to train the network to efficiently respond to operation of the system outside the normal behaviour boundaries which can be easily simulated in the model environment and not always tested in the real systems. However at later stages and since the development of a building model might not always be an easy task, available measured data will be considered as a possible source for off-line training. ANN models have been used to simulate building infrastructures, calculation of thermal comfort index (Atthajariyakul & Leephakpreeda 2005), prediction of optimal start/stop time for HVAC systems, etc. As will be explained later, the first approach taken for this stage of the research is to use the ANN to improve the set-back schedule of the facility.

ANN based controllers may be preferred over the classic Proportional, Integral, Derivative (PID) controllers for different reasons. In particular because PID controllers are typically reactive controllers, and are designed on the basis of a linearization of the model, while ANN controllers do not need any linearization of the model and can be active/predictive controllers giving the system the possibility to start reacting/optimising before the actual variation in the conditions occurs. This feature can lead to a considerable reduction in energy consumption in HVAC systems through the elimination of oscillations during transient periods.

Since the physical models used to train the ANN are always simplified versions of the reality, a fine tuning of the ANN with a measured dataset (Real dataset) is required. As a second step, it is also proposed to implement a reinforcement learning algorithm in the ANN based controller to provide an online continuous adaptation capacity to the ANN so it never stops improving its performance (Coulom 2002).

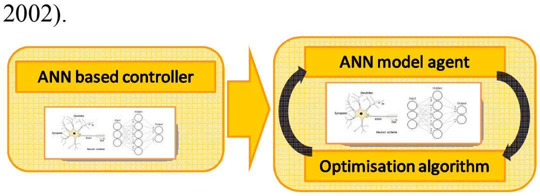

Figure 3 - ANN based controller overview

EXPERIMENT

In order to test and prove the effectiveness of the proposed methodology an initial application test has been carried out with a sport facility at the National University of Ireland, Galway (NUIG). The sport facility (Ionaid Spóirt) is owned by the university and run the by Kingfisher Club, a private company that specialises in sport facilities management. The sport facility comprises a gross floor area of approximately 8,000 m^2 distributed over two stories which includes several functional areas such as: a 25m swimming pool, sport halls, gym, studios and several courts.

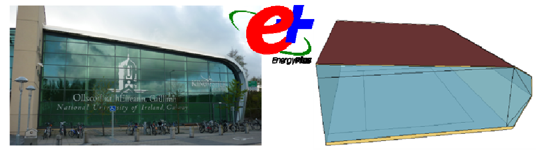

Figure 4 - NUIG swimming pool

The experiment presented in this paper focuses on the air temperature control of the swimming pool hall of the facility, which has an extension of 701.52 m^2. Two identical Air Handling Units (AHUs) constantly keep the air temperature at 30°C in the swimming pool hall. Each AHU comprises: supply and return fan (6.6 m^3/s), frost coil (73 kW), cross flow heat recovery unit and a heating coil (250 kW). The facility is open every day and occupancy is constantly monitored.

Simulating a swimming pool environment is a challenging task due to the inter relationships between water, air temperature and relative humidity in the pool hall that affect the water evaporation rate and therefore the latent load in the zone. Few simulation tools for swimming pools exist and in many cases they have limitations. TRANSYS offers one such model (Auer 1996). A recently published paper (Ribeiro et al. 2010) documents a procedure to model swimming pools in ESP-r, however ESP-r is not yet integrated in the BCVTB and for this reason EnergyPlus was used. In order to take into account the heat exchange between the water in the pool and the air in the pool hall sensible and latent load have been considered separately. The sensible load has been modelled with a surface at the constant water temperature of 29.5°C. The latent load has been hourly calculated with equation (1).

$$\dot{Q} = \dot{m}_{water} \cdot L_{evap} \cdot A_{pool} \tag{1}$$

Equation (1) calculates the total latent load as a multiplication of the water evaporation rate ($\dot{m}_{water}$) by the water latent heat of vaporization (L_{evap}) by area of the pool (A_{pool}). The water evaporation rate (2) was calculated by the analytical formulas published (Shah 2008) which consider water temperature (T_{water}), air temperature and relative humidity (T_{air}, RH_{air}), area of the pool (A_{pool}) and pool occupancy (Occ).

$$\dot{m}_{water} = f\left(T_{water}, T_{air}, RH_{air}, A_{pool}, Occ\right) \tag{2}$$

The water latent heat of vaporization (3) has been calculated using Watson's equation (Vidal 2003) which is constant because it takes into account only the water temperature and other physical properties of the water (e.g. critical temperature).

$$L_{evap} = f(T_{water} = 29.5\ ℃) = 2463.42\ \mathrm{J/g} \tag{3}$$

Since EnergyPlus does not allow to input values, which depend on other variables that are computed during the simulation a recursive approach was taken. An initial simulation was run with an initial estimation of the hourly latent load due to water evaporation, then, hourly air temperature and relative humidity were used to recalculate a more accurate latent load. This process was repeated until reaching convergence as presented in the discussion and result analysis section of this paper.

Ventilation in pool environments is mandated by regulation (day and night). For this reason, the AHUs are constantly running with 30°C set point. Optimisation scenarios for the case study focus mainly on the evaluation of night a setback temperature in the pool hall (15°C) and its impact in terms of energy consumed and relative humidity reached. In relation to the comfort, it is required that the indoor air temperature reaches the 30°C (± 0.5°C) by the opening time of the facility (7 a.m.). It is very important to evaluate the optimal EoS (End of Setback) time, when to change the set point form 15°C (setback temperature) to 30°C (temperature required during occupied hours) in order to allow the AHUs to bring the zone back to these conditions on time. The optimal EoS time is highly dependent on the inertia of the system under different indoor and outdoor conditions. To evaluate the energy and comfort impact of the set back temperature and different EoS times (presented in the discussion section), 5 different simulations were run in EnergyPlus with no set back and also with EoS at different times: 6.15, 6.30, 6.45 and 7 a.m. The ANN based controller was then used to optimally predict the EoS as described in the next section.

In this case study, the ANN model agent consists of a ANN for EoS prediction (Yang et al. 2003).

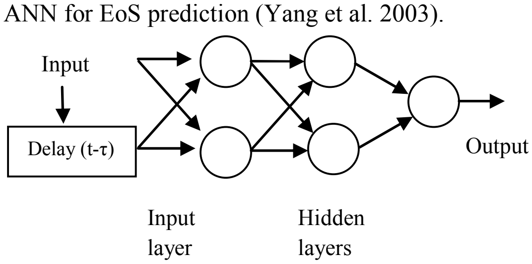

Figure 5 - ANN with delayed input basic general diagram

Introducing delayed inputs gives the ANN the necessary "memory" capability for effectively recognising sequences when dealing with time series data and produce a predicted output based on present and past inputs. In Figure 5, a basic scheme of an ANN with time delay is presented.

Figure 6 represents the simulation results with a EoS at 6.45 a.m. The pink line represents the outside air temperature while the pale blue bars correspond to the amount of time, in fractions of an hour, during which the set-point temperature is not reached in occupied hours. During most of the year, this value corresponds to 30 minutes (0.5 h in the graph) while in some summer days it is 15 minutes (0.25 h) and it is here that the ANN will optimise the operation.

Based on the results obtained in (Yang et al. 2003) and since the simulations in EnergyPlus showed a potential of improvement during the period between May and October (Figure 6) if a dynamic start time for the system were used, an ANN was developed to learn the optimal start time for the system in that period.

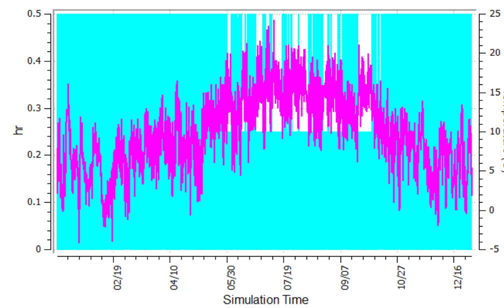

Figure 6- EnergyPlus simulation results for a EoS at 6.45 a.m.

An artificial neural network with one time step delay, 25 neurons in the hidden layer and one output was trained to determine, at every time step, how much time will pass if the system set-point were brought back to 30ºC at the present time step, to the moment it reaches the established temperature of 30ºC. The time was given in time steps of 15 minutes and possible outputs were 30 or 45 minutes. The time delay allows the system to have memory of previous events and therefore eliminates the necessity of having to manually compute the variation rate in the temperatures since they are already implicit in the delay and reduces the number of external inputs to the network.

In this experiment, the variables used as input for the artificial neural network were indoor and outdoor temperature while the target data was the time for the indoor temperature to reach the desired value. These variables were normalized to avoid prevalence of one input over the other and to reduce the range in which the artificial neural network must learn thus facilitating the learning process. As in (Yang et al. 2003) the normalization was made between values of 0.1 and 0.9 to avoid any absolute value.

The ANN model agent was trained with a data set generated with the model developed in EnergyPlus, particularly scheduling 3 cycles per day during one year in which the indoor temperature must go from 15ºC to 30ºC in the "on" cycle and from 30ºC to 15ºC in the "off" cycle. To ensure a free response of the system the control variable was the set-point of the indoor temperature. The selection of several cycles per day was done aiming at getting the broader possible range of combinations of indoor-outdoor conditions while ensuring that the system will reach steady state values before the next change in the set-point. Considerations of condensation, pool water temperature, ventilation, etc., were taken into consideration for the selection of 15ºC as the set-back set-point. Figure 7 shows the scheduled variation in the set-point utilised to generate the training data set.

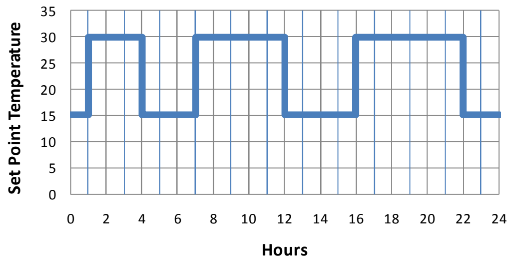

Figure 7 - Setback daily schedule for training

A simple optimisation algorithm to determine the exact start time based on the information provided by the neural network (ANN model agent) and the opening time of the facility was also developed (Figure 8).

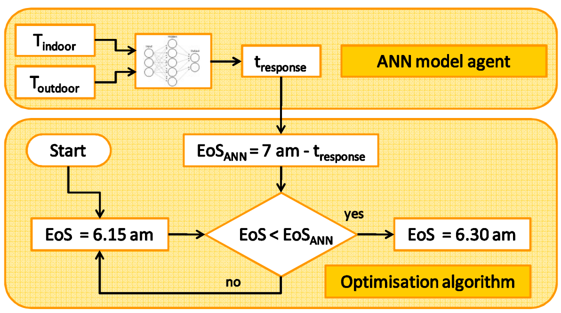

Figure 8 - Case study ANN model agent and optimisation algorithm

DISCUSSION AND RESULTS ANALYSIS

This section presents the results obtained by the application of the proposed methodology to the NUI Galway swimming pool.

The first results shown in Table 1 and Figure 9 show the effectiveness of the simulation methodology adopted in EnergyPlus for simulating the swimming pool. All the three parameters considered (water evaporation latent load, air temperature and air relative humidity) converge to zero, at different paces, with an increasing number of simulations. Table 1 and Figure 9 show the maximum hourly positive (overestimation) or negative (underestimation) variation between two different simulations for each of the considered parameter. Being these hourly values, the variation calculation compares the 8760 values of each simulation (24h * 365 days) with the 8760 of the previous simulation and identifies the percentage hourly variation. The latent load of evaporation is the parameter with the highest variation at the second simulation run (Run 2) with a max overestimation of +213.58% and a min underestimation of -25.52% and a total variation of ±239.11%.

Table 1 - Variation of Latent load, air temperature and RH, between different simulations

	Latent Load deviation		Air Temp. deviation		Air RH deviation	
	Max [%]	Min [%]	Max [%]	Min [%]	Max [%]	Min [%]
Run 2	213.6	-25.5	3.30	-0.46	38.82	-12.4
Run 3	12.56	-35.2	6.32	-4.10	7.78	-16.6
Run 4	27.61	-6.95	4.28	-5.94	11.65	-3.92
Run 5	7.89	-12.2	0.01	-0.01	2.24	-5.98
Run 6	7.69	-1.77	0.01	-0.01	3.64	-1.23
Run 7	1.01	-3.91	0.00	0.00	0.71	-2.07
Run 8	2.35	-0.56	0.00	0.00	1.25	-0.41
Run 9	0.32	-1.34	0.00	0.00	0.24	-0.71

The total variation decreases with the increasing number of simulation runs and the resulting recalculation based on more accurate air temperature and relative humidly. The final convergence after nine simulations corresponds to a total variation of ±1.66%: 0.32% (max overestimation) and -1.34% (min underestimation).

Despite an increase in total variation of the room air temperature between simulation Run 2 and Run 3, this parameter reaches quickly convergence: ±0.02% at Run 5, ±0.01% at Run 6 and ±0.00% at Run 8.

The air relative humidly total variation also decreases with the increasing number of simulation from a total variation of ±51.23% at Run 2 to a variation of ±0.95% at simulation Run 9.

This recursive calculation of water evaporation latent load, air temperature and air relative humidity has been proven to be a viable approach. However integration between EnergyPlus and the BCVTB would allow an online iterative calculation of the latent load resulting from the value of air temperature and relative humidity at each time step. This option would save simulation time.

For evaluating the impacts of different operation strategies the energy consumption metric adopted is the annual heating energy consumed by the AHUs heating coils and expressed in kWh. The occupied hours during which the air temperature set point (30ºC) was not met have been used as the metric for comfort. Table 2 shows the results of the different simulations in the physical model (EnergyPlus) and the impact of the four new operation strategies on the energy consumption and occupant comfort against current operation strategy (without setback temperature at night).

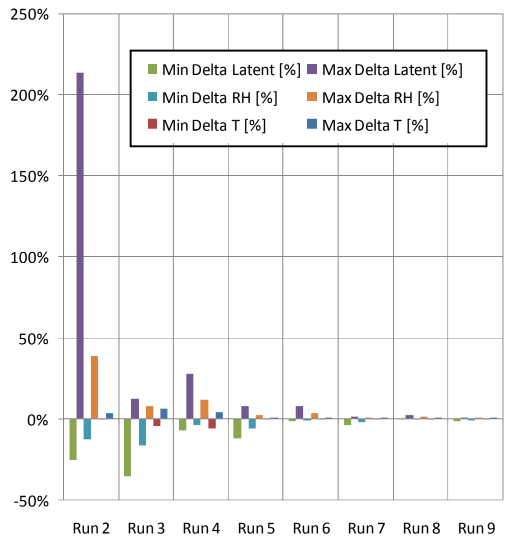

Figure 9- Variation of Latent load, air temperature and RH, between different simulations

The energy savings achieved with 15ºC of setback temperature between 22 p.m. and 6.15 a.m. correspond to 30.28% (approx 182 MWh/year). In this case there are zero occupied hours during which the air temperature set point (30ºC) is not met, therefore this strategy does not affect occupants comfort. The accurate estimation of the relative humidity has allowed to control it within the proposed schedule. RH has never been higher than maximum value of 85% recommended in literature (Arthur 1994). This is due to the constant ventilation also at night. Additional savings up to 33.77% would be possible with EoS at later times (6.30, 6.45, and 7). However, in these cases a significant reduction in the comfort condition of the zone in the early morning would be experienced when the facility is open to public with an excess of 219 hours with EoS at 7.00. In Table 2 and Figure 6 is possible to appreciate that, depending on indoor and outdoor conditions, the system takes between 30 and 45 minutes to increase the zone temperature form 15ºC to 30ºC. More specifically, there are 67 days between May and October (Figure 10) in the simulated year during which an EoS equal to 6.30 a.m. would be sufficient to reach the required set point temperature by 7.00 a.m.

As mentioned in the preceding section, the artificial neural network model agent for this case study application has been used to learn how long the system takes to bring the temperature from 15ºC to 30ºC in different conditions. The optimisation algorithm was then able to calculate per each time step (every 15 minutes) whether the set point should have been changed or not depending on the estimated heating time simulated by the ANN model agent. Based on indoor and outdoor air temperature the ANN based controller was able to identify 52 out of 67 days during which the EoS time could have been moved to 6.30. This represents an accuracy of approx 77%. The resulting yearly Heating Coil Energy with ANN based EoS was 417,187.27 kWh with 0 hours of Tset not met.

Table 2 - Energy and comfort impact of night set back temperature

	Total Heating Coil Energy [kWh]	**Energy Savings [%]**	**Occupied hours with Tset not met [h]**
No Set Back	602,983.56	-	-
EoS at 6.15	420,391.19	30.28	0.00
EoS at 6.30	413,395.25	31.44	63.25
EoS at 6.45	406,402.66	32.60	141.50
EoS at 7.00	399,344.80	33.77	219.25

CONCLUSION AND FUTURE WORK

This paper presents the overall methodology part of the SportE[2] Why Module which aims at the optimisation of energy flows and HVAC systems operation in sport facility. The initial results obtained in the demonstration case study show the effectiveness of the proposed methodology in integrating building energy simulation (to test the energy and comfort impact of different operation strategies) and ANN (to optimise HVAC system control). A 15ºC set back temperature and appropriate EoS times were identified leading to energy savings in excess of 30% in this particular and initial experiment. A procedure to simulate swimming pool in EnergyPlus was also proposed and

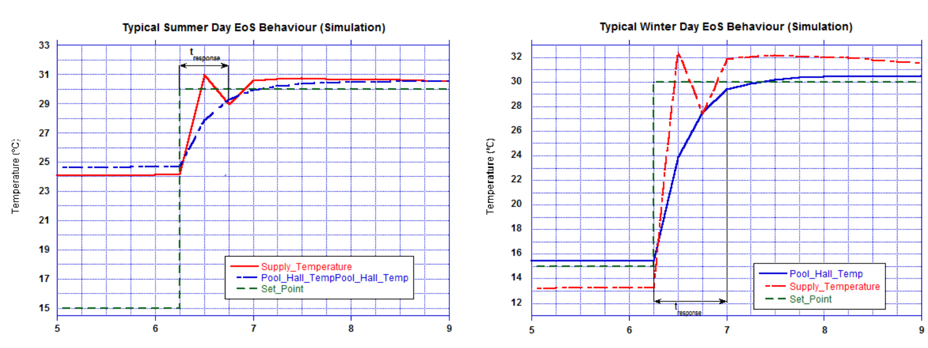

Figure 10 -Response time for typical summer day (left - 30 minutes) and winder day (right - 45 minutes)

documented. Future work is required for the integration (through the BCVTB) of an online latent load calculation. A more complete model should also consider a variable pool water temperature including its heating system and control. Additional energy savings with the utilisation of the ANN based controller are very small at this point. Therefore, to determine the effective energy impact of ANN based controller an appropriate simulation of the HVAC control system (with Modelica or Simulink) is required. As a subsequent step, optimisation scenarios in the real facility will also be scheduled in order to validate the model and fine tune the ANN with a particular focus on the system inertia. Future work with the ANN based controller will also include the designing and implementation of a Model Based Neural Network Predictive Controller to be actually acting on the variables of the system. Also the introduction of the on-line continuous learning characteristics through reinforcement learning and a methodology to allow a rapid development of the ANN controller based on real data will be studied.

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