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Deep learning optimal control for a solar-biomass system for residential buildings

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TOPIC: NUMERICAL SIMULATION AND MODELLING

1. Introduction

Nowadays, it is well known that the reduction of energy consumption in buildings is crucial to achieve a substantial reduction of gas emission to the atmosphere and decrease the fast depletion of energy sources. Indeed, buildings are responsible for almost 40% of the overall energy consumption and gas emission into the atmosphere [1], therefore, immediate actions are needed. The reduction of the energy demand through passive solutions (i.e. building envelope) has been taking into account in directives such as the Energy Performance of Buildings Directive [2]. However, the generation of energy through efficient systems and the use of renewable sources is also required to achieve deep decarbonisation of the grid. However, the main disadvantage of renewable sources is represented by their daily and seasonal intermittency. Therefore, a system that allows the combination of more of them can provide a higher flexibility and increase the total share of renewables to meet energy needs in buildings.

In this context, the EU-funded H2020 project SolBio-Rev aims to develop an energy system based on the use of solar energy and biomass to provide heating, cooling, domestic hot water, and electricity to increase the share of renewable sources for different building typologies in different climates. In order to achieve high efficiency, the system combines different technologies including: a reversible ORC/heat pump, solar collectors with thermoelectric generators, and last generation biomass boiler. The potential of the SolBio-Rev system was studied by Palomba et. al [3,4], where the optimal system configuration for different EU climates and building typologies was defined to achieve a 100% renewable future scenario. However, in order to maximize the use of renewable sources, the implementation of a control strategy that optimizes the use of the different components is essential. In this case, different control strategies can be found to manage energy systems [2] and, beyond standard rule-based control, one of the techniques that gained attention recently is Model Predictive Control (MPC). However, MPC requires specialized solvers to find optimal solutions that are limited to only a certain type of non-linearities. Deep Reinforcement Learning (DRL) proved to be successful for solving complex control problems that make it become a hot topic in the field of energy system control. Under this scope, it is possible to find DRL architectures approximating Model Predictive Control (MPC) on complex systems, or DRL algorithms that successfully control an HVAC (heating, ventilation, and air conditioning) system for a given user comfort requirement [5]. A DRL architecture was successfully applied in a previous study by the authors [6] to deal with the complexity of an innovative hybrid energy storage system and to derive appropriate high-level control policies, able to minimize the operational cost of the system. In this study, DRL techniques were used to develop an optimal control under demand response in the SolBio-Rev system in order to minimize the operational cost during summer and winter.

2. Materials and method

2.1 System description

The SolBio-Rev system developed for Mediterranean climate is shown in Figure 1. It consists of the following main components with the respective functions:

- Solar collectors with thermo-electric generators (TEGs) providing 1) heat to a short-term storage tank that is connected to the sorption chiller, the biomass boiler, and the domestic hot water (DHW) distribution system and 2) electricity to auxiliary system components (i.e., pumps).
- Biomass boiler that supplies DHW and space heating (based on radiant floor) to the user.
- Sorption chiller that works in cascade with the reversible heat pump during summer operation.
- Reversible heat pump to provide heating/cooling.
- Dry cooler, which provides evaporation heat to the heat pump during winter operation and dumps condensation heat to the ambient during summer operation.
- Buffer tank to decouple the heat pump and the short-term storage tank from the heating/cooling distribution system.

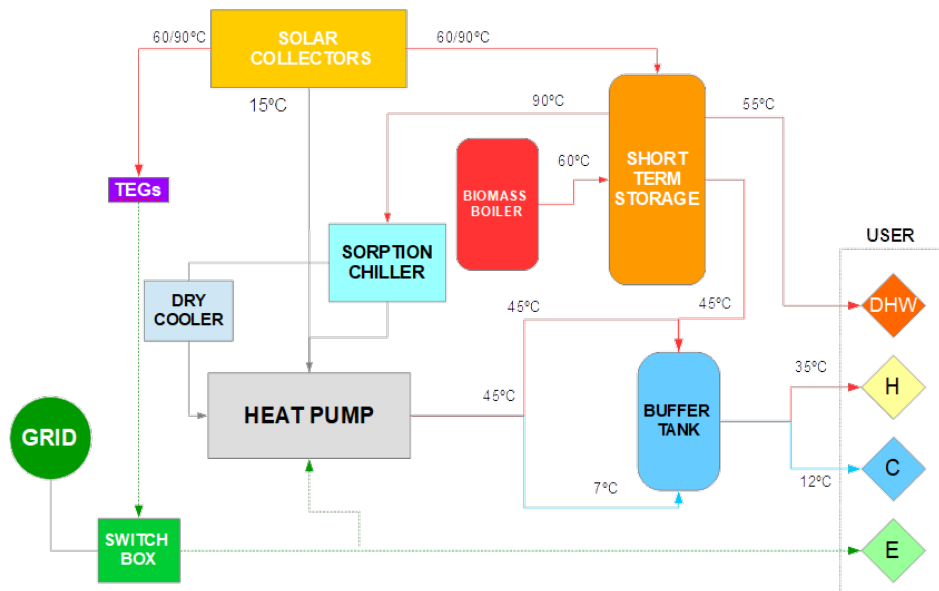


Figure 1. System components for the SolBio-Rev designed for Mediterranean Climate

The solar collector model is based on a commercial AkoTec OEM vario 3000-20, and the solar thermal power was calculated based on the global solar radiation and the overall efficiency of the solar collectors. The thermoelectric generators were modelled considering the total thermal resistance of the TEGs system and calculating the power output via a linear function related to the temperature difference between input and output. The heat pump and the adsorption chiller were modelled via performance curves given as polynomial functions based on equations for the cooling power and coefficient of performance (COP) as a function of operating temperatures. The

biomass boiler was considered to operate at constant power with a 98% thermal efficiency. The two water storage tanks were model using the energy balance between the inputs and outputs. The models were programmed in Python [7] and the connection of the subsystem in the numerical code was done verifying the correct execution of the possible operational modes.

The sizing was done considering the energy demand for heating, cooling, and DHW of a residential building (multi-family house) taken from the EU project iNSPIRe [3] and located in Madrid (Spain), considering the U-values of a new/refurbished building according to the building directive. The energy demand for heating, cooling, and DHW for all year are shown in Figure 2 and Figure 3. The sizing of the SolBio-Rev system considered is summarized in Table 1.

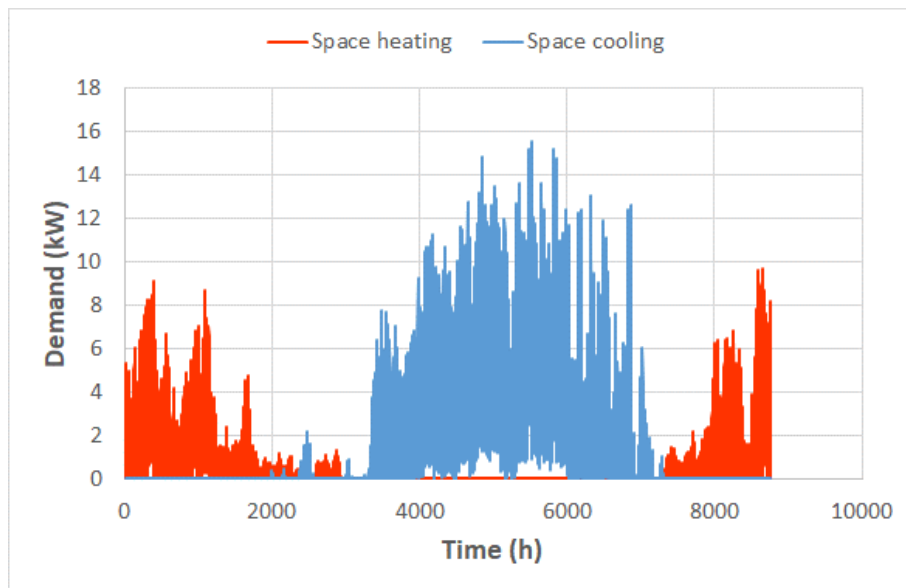


Figure 2. Space heating and cooling demand of the modelled reference building

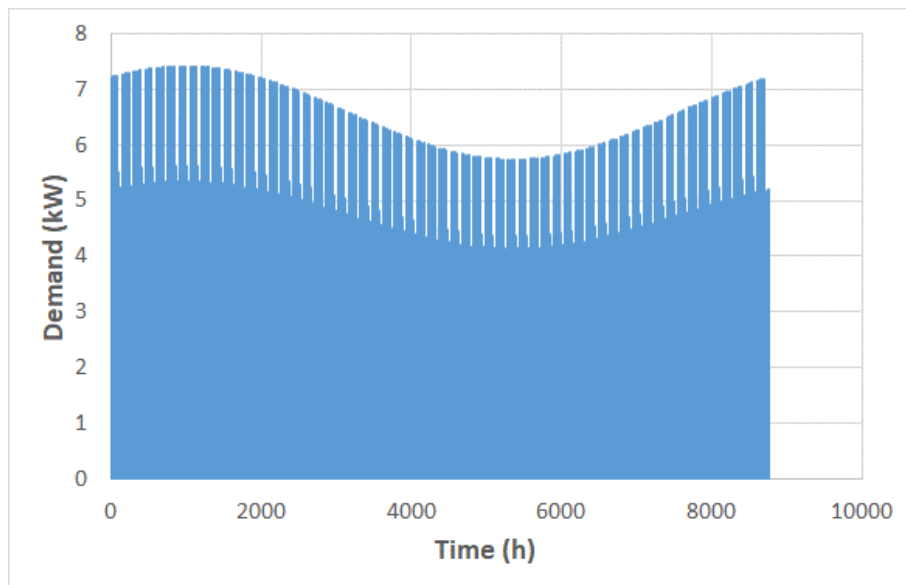


Figure 3. DHW demand of the modelled reference building

Table 1. Size of the SolBio-Rev system components

Component	Size
Adsorption chiller	15 kW
Biomass boiler (without supplying heat to the ORC)	15 kW
Reversible heat pump	15 kW
Solar collectors with TEGs	50 m ²
Storage tank	1500 litres
Buffer tank	800 litres

The system modelling considers two different time scale slots: a finer time slot (3 minutes) to numerically compute the SolBio-Rev system behaviour for inner model operations, not relevant for control purposes; and a second longer time slot (15 and 30 min were considered) to manage the high-level control system. Within the longer time slot, any action decided by the control system will not change until any of the subsystem limits is attained. The input and system variables considered as an input in the control are summarized in Table 2. The set of actions that are taken by the control algorithm are based on the combination of operational modes of each subsystem/component described in Table 3.

Table 2. Variables (input and state variables)

Variables	Input Unit
Solar irradiance	W/m ²
Ambient temperature	°C
Temperature at bottom level of the short-term tank	°C
Temperature at middle level of the short-term tank to supply space heating	°C
Temperature at top level of the short-term tank to supply DHW/heat to the sorption chiller	°C
Temperature of the buffer tank	°C
DHW profile	[0,1]
Space heating (SH) demand profile	kWh
Space cooling (SC) demand profile	kWh

Table 3. Operational modes of the system components

	State no.	Description
Solar collectors + TEGs	0	Off
	1	Setpoint 60 °C (SH+DHW)
	2	Setpoint 90 °C (sorption chiller)
	4	Feeding TEGs for electricity generation
	5	Setpoint 15 °C - Solar-assisted operation of heat pump for heating
Heat pump	0	Off
	1	On for space heating using dry cooler
	2	On for space heating using solar collectors
	3	On for cooling using dry cooler
	4	On for cooling using sorption chiller
Biomass boiler	0	Off
	1	On for short-term storage tank charging at 60 °C
Buffer tank	0	Not charging
	1	Heat provided from the short-term storage tank
	2	Heat provided from the heat pump
	3	Cooling provided from the heat pump

Control policies focused on the minimization of the operational costs of the system (€), using a cumulative reward function calculated based on the costs associated to running the system in different operational modes. The objective function can be defined as in the following equation:

$$Penalty \cdot (E_{dhw} - E_{dhw,supplied}) + Penalty \cdot (E_{sh} - E_{sh,supplied}) + Penalty \cdot (E_{cooling} - E_{cooling,supplied}) + E_{boiler} \cdot Cost_{pellets} + E_{grid} \cdot Cost_{grid} \quad (1)$$

where $Penalty$ (€/kWh) is a constant (in €/kWh) that quantifies the subjective cost for not meeting the energy demand requirements. It is a design parameter for the control policy, understanding that the higher the penalty the more effort will put the control policy to meet the energy demand requirements. In this study, a value of 1 €/kWh was used as a penalty, which is much higher than the energy price itself, avoiding in this way the lack of energy supply when possible. E_{dhw} (kWh) is the DHW demand, $E_{dhw,supplied}$ (kWh) is the energy supplied for DHW by SolBio-Rev system, E_{sh} (kWh) is the SH demand, $E_{sh,supplied}$ (kWh) is the energy supplied for SH by SolBio-Rev system, $E_{cooling}$ (kWh) is the SC demand, $E_{cooling,supplied}$ (kWh) is the energy supplied for SC by SolBio-Rev system, E_{boiler} (kWh) is the energy provided by the biomass boiler, $Cost_{pellets}$ (€/kWh) is the costs of the pellets, E_{grid} (kWh) is the electricity consumed from the grid, and $Cost_{grid}$ is the price of the electricity (€/kWh). The smart control was trained using the energy demand simulated for the reference multi-family house showed above using the weather data obtained from Meteornom database for the location of Madrid [8]. The smart controller algorithm developed minimizes the objective function defined as cumulative reward of the whole year, providing the optimal policy of actions. In this case, the following assumptions were made:

- $Cost_{pellets} = 0.30$ €/kg
- $Cost_{grid} = 0.15$ €/kWh (off-peak periods) and 0.30 €/kWh (peak periods)

3. Results and discussion

To evaluate the performance of the DRL control policy, a rule-based control (RBC) policy was first implemented for the different operational modes (Figure 4 and Figure 6). To assess the RBC policies, exactly the same number of training and testing data and the same time-step for the control management were used. In particular, the data sets were created considering 150 days for winter and 80 days for summer, respectively. From each season set, days were shuffled and 10 days were taken for testing and 10 days for validation. The remaining days of each set were kept for training the algorithm. The results shown in this study correspond to the validation set. The effective actions and the total cost associated to the smart control policy for winter season and summer season are shown in Figure 5 and Figure 7, respectively. By comparing the effective actions of the RBC and the smart control policies, it is possible to notice that during winter the smart control reduces the use of the biomass boiler, and the solar collectors are mostly operated to use the heat pump in solar assisted mode, while the RBC uses sometimes the solar radiation to run the TEGs. This allows to decrease the total cost from 237 € to 206 €. In summer, due to the continuous need of cooling demand, the heat pump is most of the time on. However, using an RBC policy, the heat pump always works using the dry cooler, while the smart control is able to exploit the cascade mode with the sorption chiller. However, the energy used to drive the sorption chiller for the cascade mode slightly penalizes the energy available for DHW, highlighted by the higher use of the biomass boiler. Therefore, in summer, the total cost using the smart control increases from 274 € to 287 €.

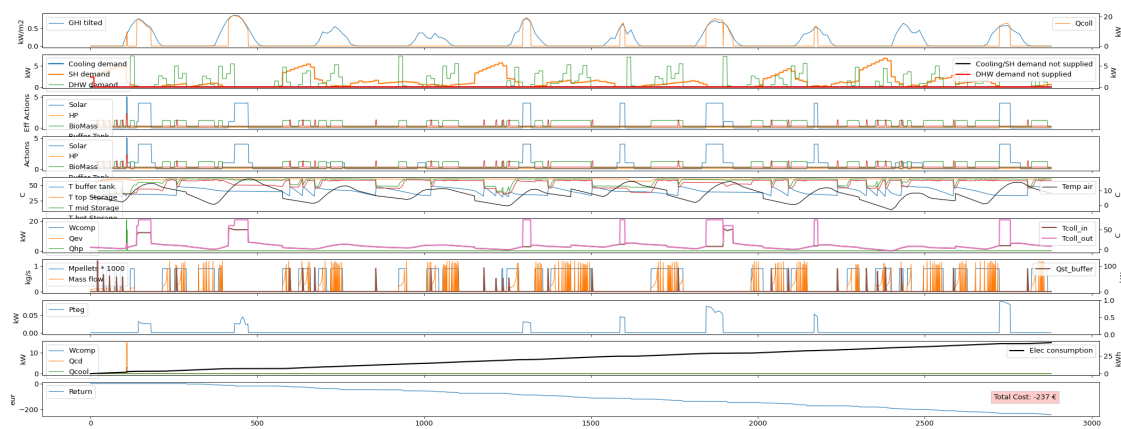


Figure 4. Effective actions and total cost of the RBC policy for winter season

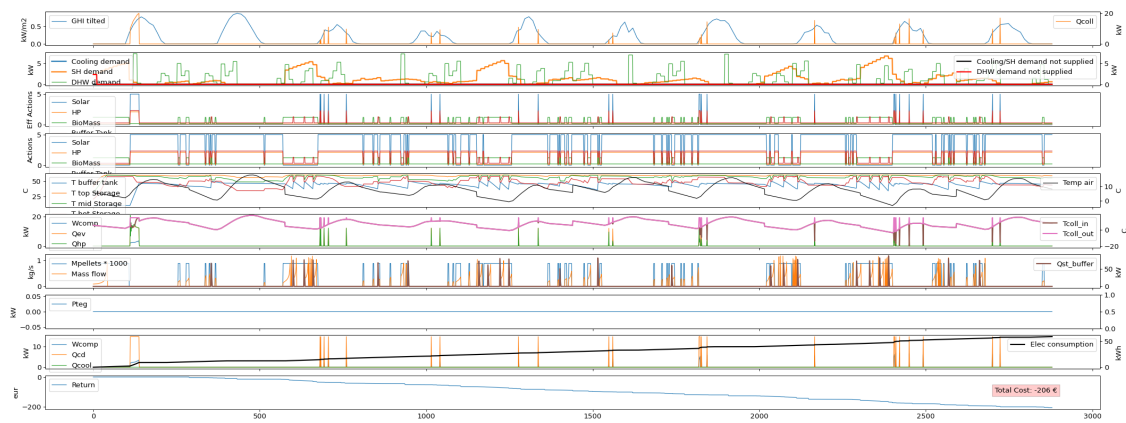


Figure 5. Effective actions and total cost of the smart control policy for winter season

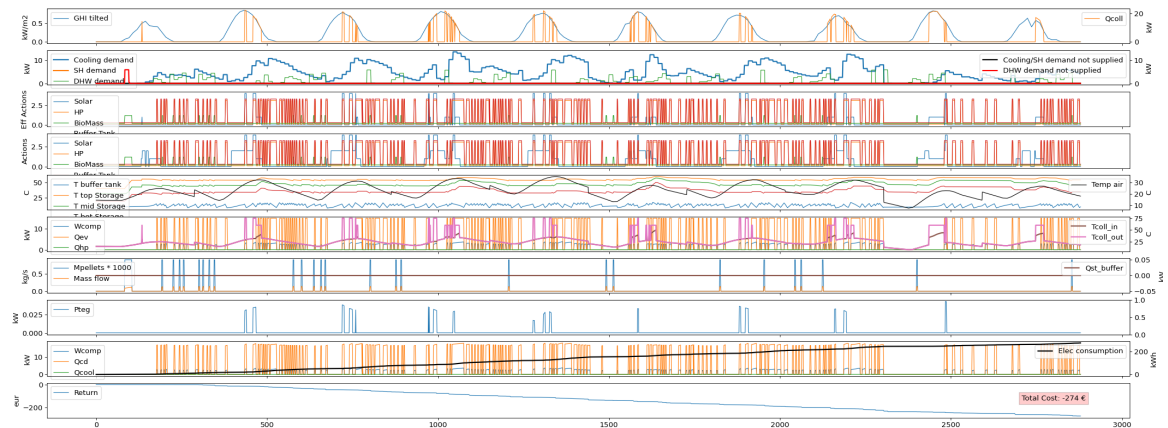


Figure 6. Effective actions and total cost of the RBC policy for summer season

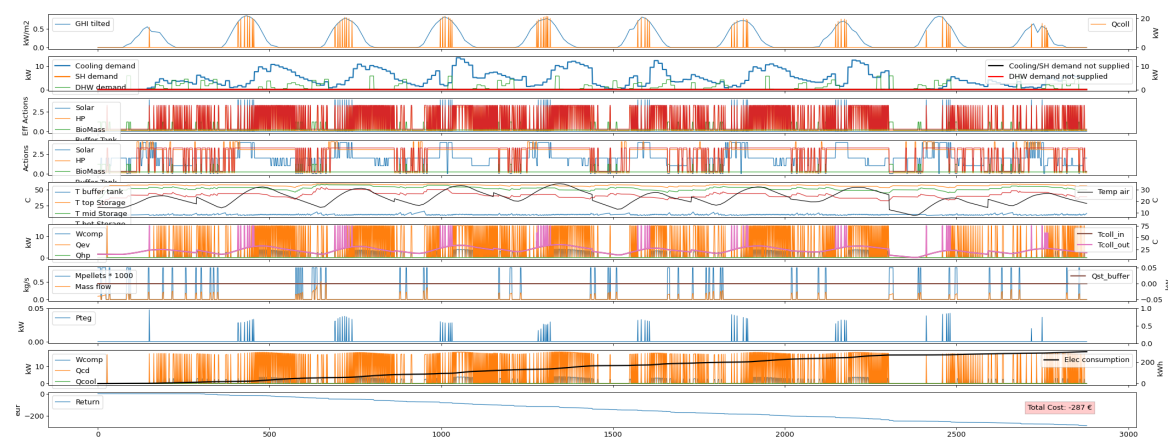


Figure 7. Effective actions and total cost of the smart control policy for summer season

4. Conclusions

Hybrid energy systems that combine more renewable energy sources are able to provide a high flexibility and increase the total share of renewables to meet energy needs in buildings. The project SolBio-Rev aims to develop an energy system based on the use of solar energy and biomass to provide heating, cooling, domestic hot water, and electricity for different building typologies in different climates. In this study, deep reinforcement learning techniques were used to develop optimal control policies of the SolBio-Rev system to minimize the operational cost during all year. To evaluate the performance of the DRL control policy, an optimized rule-based control policy was first implemented considering the different operational modes of the system components. The results showed that, compared to the RBC, the smart control is able to reduce the total cost in winter from 237 € to 206 € for 10 days of operation by reducing the operation of the biomass boiler. However, in summer, the total cost using the smart control slightly increases from 274 € to 287 € due to the higher use of the biomass boiler. Therefore, on-going study focuses on improving the smart control strategy to be able to also reduce costs in summer.

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