A Novel Deep Learning-Based Technique for Smart Control of Heat Pumps Integrated into Solar District Heating Systems

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Abstract:

District energy systems provide many options for integrating renewable energy sources and energy storage systems into residential and commercial buildings. Solar district heating systems (SDHSs) contribute to the deployment of large-scale solar energy-based technologies. SDHS technical challenges during operation may occur due to not optimal control. Nevertheless, they can be overcome with smart control of an integrated heat pump. To address this problem TRNSYS (transient system simulation) software was used to develop the SDHS model; the system operates by employing a smart control approach for the heat pump, which is coupled to thermal storage tanks for domestic hot water and space heating to meet community demand. The methodological approach has been applied to an SDHS in Madrid (Spain) to provide for the heating demands of a neighbourhood that consists of 280 apartments in order to more effectively illustrate the abilities of the proposed control strategy. The present work focuses on the development of a co-simulation framework based on TRNSYS and Python for offline training of a control strategy based on deep reinforcement learning algorithms for a smart agent that will control the integrated heat pump into SDHS with seasonal storage system. The work will consider the life cycle cost analysis for the technical economic evaluation for the proposed control strategy. Results will show if the heat pump DRL-based control offers significant techno-economic benefits, compared to traditional control strategies.

Keywords:
solar district heating systems, thermal energy storage, heat pump, deep reinforcement learning, life cycle cost analysis

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1. Introduction

District energy systems offer various options for integrating energy storage and renewable energy sources into residential and commercial buildings [1]. Solar communities with seasonal thermal energy storage [2] and solar thermal systems [3] are examples of such systems that can facilitate the advancement of fourth and fifth-generation district heating systems [4], [5]. Systems for district heating powered by solar energy help in the deployment of large-scale solar energy-based solutions. In fact, several prosperous large-scale solar district heating systems (SDHSs) are currently in use in nations including Austria, Canada, China, Germany, and Denmark [6]. Tian et al. [7] highlighted two successful large SDHSs. Even though the modeling and design of these systems have been thoroughly studied recently [8], [9], more research is needed to develop advanced control techniques for solar district heating systems.

Techniques for controlling HVAC (heating, ventilation, and air conditioning) are complex due to the way the system's components interact with one another and with the thermal dynamics of buildings. The continuous adjustment of the heating or cooling system while maintaining the comfort levels set by the occupants is one technique to reduce the amount of energy used for space conditioning. The conventional method for control, which is rule-based control (RBC), typically involves simple hysteresis loops that reheat or cool the building every time the temperature reaches a threshold.

Model predictive control (MPC) improves the control technique by allowing the use of predictions from outside variables like the weather, the electricity price, etc. This leads to a wider range and more efficient control compared to RBC. The primary aim is to control building temperature, with cost optimization being a secondary goal. While MPC outperforms RBC regarding its operation capability, it complicates the system and requires the availability of a model that accounts for the system dynamics. Due to the complexity of building thermal dynamics and heterogeneous environment disturbances, the classical rule-based and model-based approaches are frequently ineffective in practice [10].

Another control method is reinforcement learning (RL) which is a model-free approach where the agent learns the optimal action to take by "trial and error" without the need for previous knowledge of the system or process. Model-free methods can operate without a model of the environment [11]. RL techniques can learn by interacting with its environment and do not require any supervision. In recent years and within many fields, RL has become a strong alternative to MPC. The fundamental idea behind RL is that the optimal behavior or action is encouraged by way of a positive reward, while the least desirable action is punished by a negative reward [12], [13].

The drawbacks of conventional RL can be overcome by deep reinforcement learning (DRL), which enhances RL with deep neural networks to approximate the value function and policy function when those are hard to model due to the dimensionality of the problem. Therefore, the DRL approach is more suitable and flexible in terms of control strategies than traditional control approaches. DRL has been utilized extensively in both the business and academic fields, such as, in robotics [14], gaming [15], industrial systems [16], and autonomous vehicles [17].

The present work focuses on the development of a co-simulation framework based on TRNSYS (transient system simulation) and Python for offline training of a control strategy based on deep reinforcement learning algorithms for a smart agent that will control the integrated heat pump and seasonal storage system of a SDHS. The work will consider the life cycle cost analysis for the technical economic evaluation of the proposed control strategy.

2. Materials and method

This section describes the system's details and the methodology used for system modeling and control.

2.1. Energy system description

An overview of the analyzed systems is presented in Figure 1. The main components of the system are the solar thermal collector (COL), the DHW storage tank (DHWT), a half-buried sensible seasonal storage tank (SST), an auxiliary natural gas heater (AUX), and a water-to-water heat pump unit (HP). This SDHS model was designed and based on the system proposed by Abokersh et al. [18] and Tulus et al. [19].

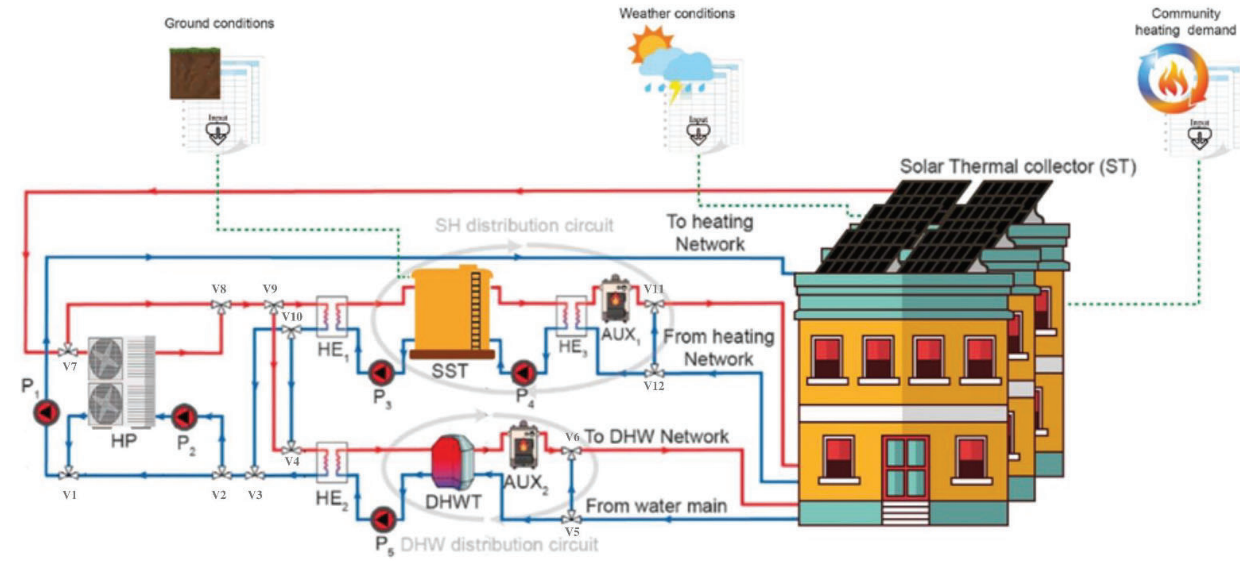

Figure. 1. An overview of the HP with SDHS integration's design.

As seen in Figure 1, the heat pump (HP) functions as a heat source for the SST when connected with the solar field circuit. In this arrangement, the district's space heating (SH) or domestic hot water (DHW) demand can be accomplished efficiently by the thermal energy collected from the COL or it can be stored in the SST. An adequate design of the heat pump that is incorporated in SDHS is required to meet the SH and DHW needs of a hypothetical residential neighbourhood throughout the year. The heat from solar collectors is transferred to the DHWT in the DHW operation mode, with the intervention of P1, P2, and P5 pumps through and switching on the following valves V1, V2, V3, V4, V5, V6, V7, V8, and V9. The AUX2 is activated with the help of V5 and V6, when solar thermal energy is insufficient to meet the demand in the DHW network. The HP unit is inactive while in DHW mode. In SH operation mode, heat is transferred from ST to SST through HE1 using pumps P1, P2, and P3 and valves V1, V2, V3, V8, V9, and V10. Under particular circumstances, the heat generated by the HP is either provided to the SST for charging up the heat stored or delivered directly to the SH. While the daily DHW demand is supplied by the short-term storage DHWT, the SH demand is supplied throughout the winter by the SST. Here, it is crucial to remember that the heat provided for the SH is at a low-temperature level (50 °C), whilst the heat supplied for the DHW is at a high-temperature level (60 °C). Finally, the auxiliary heater acts as a supplement if the solar field, SST, and HP are incapable of providing the required amount of heat.

2.2. Co-simulation TRNSYS-Python framework

TRNSYS (transient system simulation) program is a tool, for simulating an energy system's dynamic behavior. In the simulation studio, TRNSYS's components are linked graphically to solve algebraic and differential equations. The TRNSYS simulation environment's dynamic nature helps to introduce the SHDS model in a more realistic manner. This software does, however, have significant limitations when it comes to the development and optimization of HVAC system control. Some intelligent control algorithms, such as DRL-based control approaches, are inconvenient and difficult to use directly in the built-in software [20].

In order to address this issue, a co-simulation testbed with a SDHS TRNSYS model and DRL-based control approach has been built in order to enable dynamic data transfer and interaction between these two systems as depicted in Figure 2. As DRL-based training requires a large amount of training data, (i.e., of simulations), those simulations would have to be done in parallel to maximize computational resources usage and to reduce the required time for the experimentation. In order to control such simulations and to be able to train the DRL control software, they have been developed, following the de facto standard for DRL training, as a Gym environment [21].

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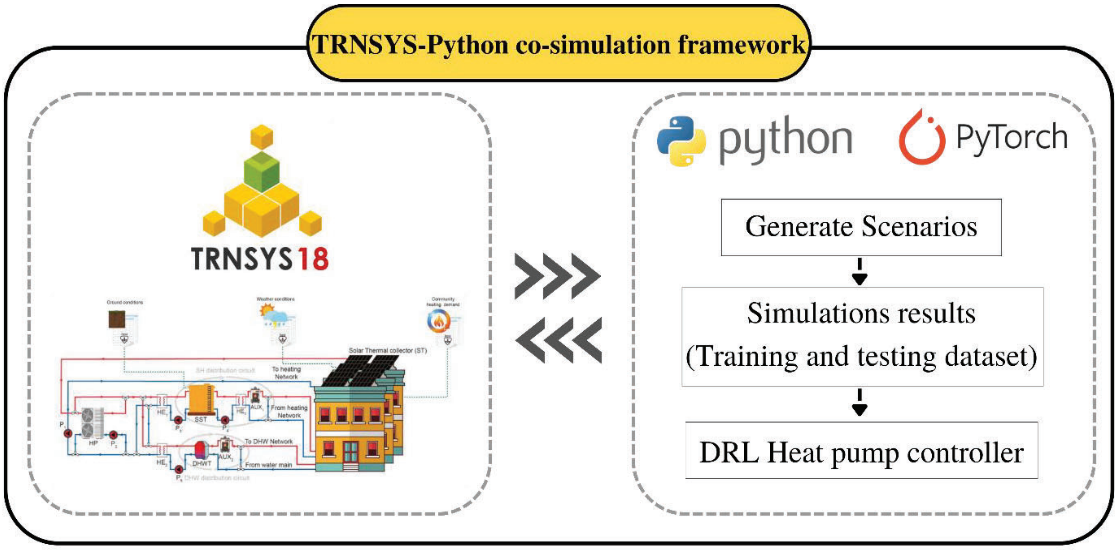

Figure. 2. TRNSYS-Python co-simulation framework.

2.3. Life cycle cost analysis

In the present study, the life cycle costing (LCC) methodology is employed to conduct the economic evaluation of the proposed control strategy of the integrated heat pump integration into a community sized SDHS, which is based on the work of Tulus et al. [19] and Abokersh et al. [18].

The fundamental concept of the LCC technique involves using a future cost approach. This involves calculating the present value of all the expenses incurred over the lifespan of the system, using a discounting method. By adding the initial capital cost (IC), operational cost (OC), maintenance cost (MC), and total equipment replacement cost (RC), we can estimate the net present cost (NPC).

$$NPC = IC + OC + MC + RC \tag{1}$$

The initial capital cost refers to the cost of investment at the beginning of a project. This cost includes the cost of purchasing the equipment, its installation and transportation, as well as any contingencies expenses:

$$IC = (1 + \alpha_{CF}) + \sum_K (PEC_K . FBM_K) \tag{2}$$

In the given equation, PEC_k refers to the initial cost of purchasing equipment unit k, FBM_k represents the bare module factor that takes into account the costs associated with installation and transportation, while α_{CF} is the contingency fees factor. The PEC_k value is adjusted to its present value from the base year (year A) to the year of installation (year B) using the Chemical Engineering Plant Cost Index (CEPCI) [19], with the help of the following equation:

$$PEC_K = PEC_K^{year\ A} \frac{CEPCI^{year\ B}}{CEPCI^{year\ A}} \quad \forall k \tag{3}$$

The operational cost (OC) refers to the total amount of yearly operating expenses that includes the maintenance costs for various equipment units and facilities, the consumption of electricity by hydraulic equipment, and the usage of natural gas by auxiliary heaters. This cost can be stated using the following equation:

$$OC = C_M PWF_M + C_P PWF_P + C_{AUX} PWF_{AUX} \tag{4}$$

In the given equation, C_M, C_P, and C_{AUX} represent the yearly expenses associated with maintenance, hydraulic equipment (such as pumps), and auxiliary consumption costs, respectively. To account for inflation and the time value of money, the present worth factor (PWF) is calculated, taking into consideration the proposed system's lifetime (Ne), inflation rate (i), and discount rate (d), which can be expressed as follows:

$$PWF = \begin{cases} \frac{1}{d-i}\left[1-\left(\frac{1+i}{1-d}\right)^{N_e}\right] & \forall_i \neq d \\ \frac{N_e}{1+i} & \forall_i = d \end{cases} \tag{5}$$

During the operation of the proposed SDHS, certain pieces of equipment have a high rate of depreciation and will require replacement. The cost of replacing them can be calculated using the following equation, which takes into account the present value of the equipment:

$$RC = PVF_n \sum_K (PEC_K . FMB_K) \tag{6}$$

The present value factor of future cash flows in year n is denoted as PVF_n. In this present work, the solar collectors, DHW storage tank, heat pump, heat exchangers, and auxiliary heaters are among the equipment that will require replacement due to their fast depreciation rate over the system's lifetime. PVF_n can be expressed as follows:

$$PVF_n = \frac{(1+i)^n}{(1+d)^n} \tag{7}$$

2.4. Case study

The methodological approach has been applied to an SDHS in Madrid (Spain) to provide for the heating demands of a neighborhood that consists of 10 buildings in order to more effectively illustrate the abilities of the proposed framework. This case study has already been described in a former article where more details can be found [18]. Each building has 28 apartments, each of which has 90 m^2 of usable space [22] and is equipped with a DHW system and radiant underfloor heating system to meet the requirement for space heating (SH) and domestic hot water (DHW) at 50 °C and 60 °C, respectively. Each building requires yearly 191.34 MWh of heating. Based on Tulus et al. [19] and Abokersh et al. [18], the proposed SDHS was previously validated.

2.4.1. Heating demand profiles

In order to compare the proposed DRL-based control strategy to the rule-based control strategy in Abokersh's study [18] the SH and DHW inputs will remain the same. Figure 3 shows the monthly DHW and SH demand for a neighborhood in Madrid that consists of 280 residential apartments.

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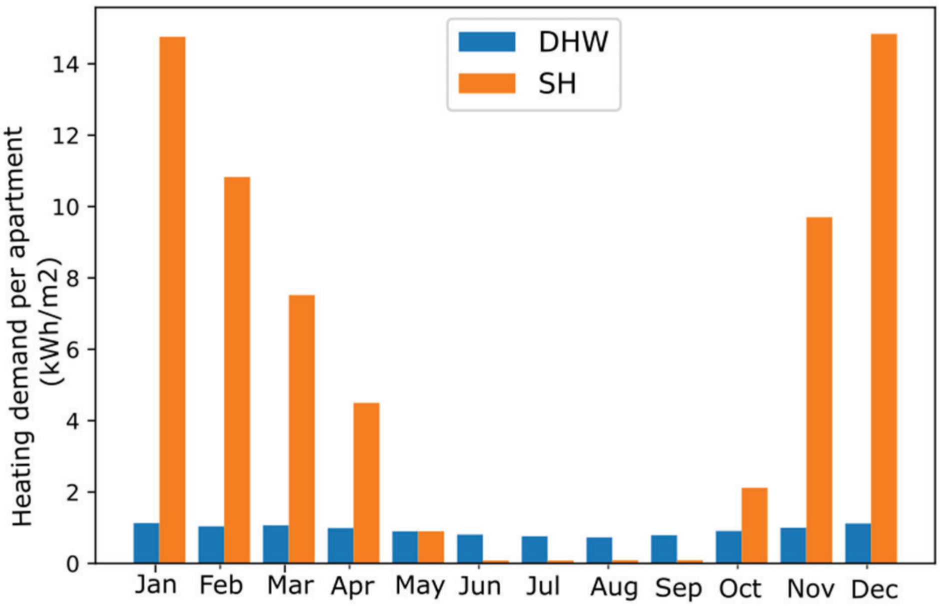

Figure. 3. Demand profiles for domestic hot water and space heating per month for a neighbourhood of 280 apartments in Madrid.

The Energy Plus database is used to gather the weather data for Madrid. This includes the incident solar radiation, ambient temperature, relative humidity, and other pertinent information.

3. Results

In this phase, using the Madrid case study in a residential community of 280 apartments the design variables of various equipment components are taken into account. While formulating the optimization problem, we are testing whether the HP smart control strategies can improve the techno-economic viability of SDHS.

Figure 4 illustrates the optimum system costs for various Net Present Cost terms and payback periods. A clear tradeoff between the proposed objective functions is indicated since the movement from scenario 1 to 5 at both traditional controls (A) and (B) increases the total cost. Thus, Abokersh et al.[18] Pareto's optimal solutions appear to provide a modest economic benefit that provides an opportunity to make improvements on system controlling, which is the objective of our proposed smart control strategy using the deep reinforcement learning algorithm.

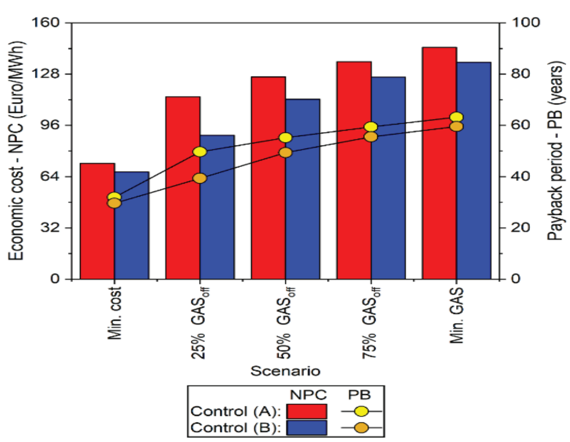

Figure. 4. The economic benefits and the payback period for the optimal Pareto solutions of the HP integrated with SDHS under control strategy (A) and (B) *[18]*.

In addition to calculating the financial gains, the proposed methodology also determines how each technology can operate at its optimal level. Hence, a figure will be illustrated to depict the percentage of grid electricity, fossil fuels (natural gas), and solar energy, following the example in Figure 5.

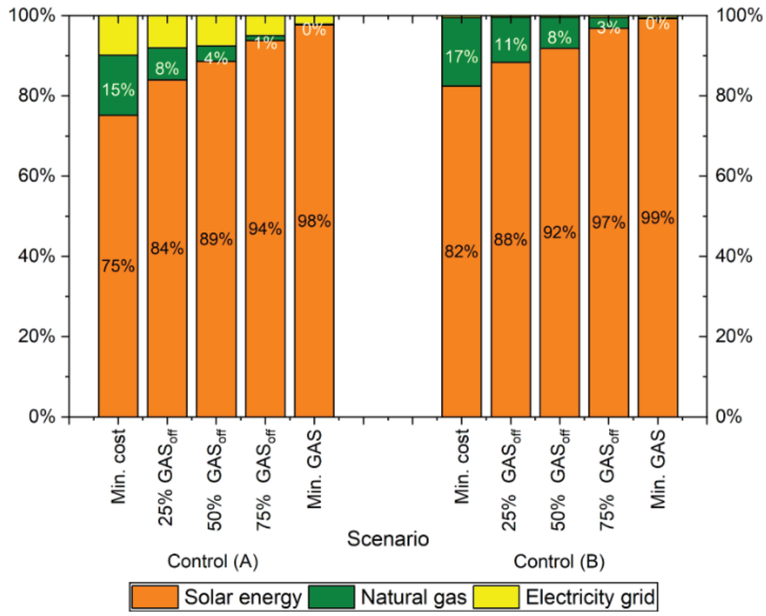

Figure. 5. The share of technologies for the optimal Pareto solutions of the HP integrated with SDHS under control strategy (A) and (B) *[18]*.

We are currently starting the model training and hope to have the results ready when the conference takes place.

4. Conclusions

The current study aims to develop a dynamic model for a solar district heating system (SDHS) integrated with a heat pump in Madrid (Spain), to provide the heating demands of a small community of 280 apartments. A co-simulation framework using TRNSYS, and Python was developed to evaluate the benefits of a smart control strategy based on a deep reinforcement learning algorithm, which will control the heat pump. The current situation can be characterised by concluding the methodology development and initiating the model training. The following step will be to evaluate the control strategy from an economic point of view by way of the life cycle cost analysis.

The aim of this study is to assess the advantages of the proposed smart control strategy using artificial intelligence in terms of technical performance and cost-effectiveness, as well as to determine if the control strategy offers significant benefits over traditional methods. The results of the study could make the solar district heating system a more feasible solution in the market, particularly in light of current policy changes on natural gas prices.

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Nomenclature

AUX	*auxiliary heater fueled by natural gas*
COL	*solar collector field*
DHW	*domestic hot water*
DHWT	*domestic hot water storage*
DL	*deep learning*
DRL	*deep reinforcement learning*
HE	*heat exchanger*
HP	*heat pump*
HVAC	*heating, ventilation, and air Conditioning*
LQR	*linear-quadratic regulator*
MPC	*model predictive control*
P	*centrifugal pump*
RBC	*rule-based control*
RL	*reinforcement learning*
SDHS	*solar district heating system*
SH	*space heating*
SST	*seasonal storage tank*
TES	*thermal energy tank*
TRNSYS	*transient system simulation program*

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