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A review of advanced ground source heat pump control: Artificial intelligence for autonomous and adaptive control

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ABSTRACT

Geothermal energy has the potential to contribute significantly to the CO_2 reduction targets as a renewable source for building heating and cooling but is yet under exploited, mostly due to its high initial investment cost. A lot of research is being carried out to optimise Ground Source Heat Pump (GSHP) systems' design, but a good control strategy is also fundamental to achieve long-term performance and reduced payback time.

GSHP control optimisation is a non-linear dynamic optimisation problem that is influenced by multiple parameters. It can thus not be fully optimised with traditional methods. Artificial Intelligence, and in particular Machine Learning, is suited for this type of optimisation as it can learn implicit relations between parameters and can address non-linearity.

This paper reviews the challenges of GSHP control and the strategies for control optimisation found in the literature, from basic rule-based system to artificial neural network-based strategies. Two principal uses of Artificial Intelligence for ground source heat pump control are identified: building a predictive model of the system that reflects its real performances and optimising the control decision in real time.

However, the examples found in the literature are limited and the need to further explore the benefits of Machine Learning is identified. The latest developments in the field are reviewed to explore their potential to further improve GSHP control. The challenges of the full implementation of such algorithms are also discussed.

1. Introduction

In Europe, all new buildings are required to be Nearly Zero Energy Buildings (nZEB) since 2020, roadmaps are implemented to convert existing buildings to nZEBs [1], and the trend is towards positive energy buildings [2]. nZEB, having high energy performance and sourcing the little energy they require mostly from renewable energies, are necessary to achieve the 2050 CO_2 reduction targets.

Geothermal energy is a key source of renewable energy for nZEBs, but is still largely underexploited [3]. Ground Source Heat Pumps (GSHP) have been installed in commercial and residential buildings because they present an energy efficient alternative to other Heating Ventilation and Air Conditioning (HVAC) systems [4], but the rate of new installations is below the desired targets [3]. One of the barriers for a wider implementation of GSHPs is that, although it is economically viable on the long term and environmentally more interesting than other alternatives, it requires a high initial investment due mostly to drilling costs [5].

Optimal design of GSHPs to obtain good economic and environmental performances has been studied extensively in the literature [6]. A less studied aspect is to optimise the control of GSHPs, thus reducing operating costs by optimising the operation time of the heat pump and taking full advantage of the building thermal inertia. Indeed, studies indicate that unsuitable control is one of the reasons GSHPs are underperforming [7]. Without proper control, there is a risk of GSHP never providing payback, as shown in [8], where the original Building Management System (BMS) resulted in the gas boiler being used as a primary heat source, never triggering the GSHP.

One category of algorithm of special interest are control strategies based on Artificial Intelligence (AI). Indeed, AI enables to learn optimal operation considering a vast number of parameters without studying all the possible cases. AI implementation for HVAC systems has been studied for the past two decades [9] and control was one of the applications of AI for GSHP identified by Zhou et al. [10]. To date only a few of the many AI techniques available have been implemented for GSHP.

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The aim of this paper is to identify the potential of the latest developments in the field of AI to improve GSHP operation. The specific challenges linked with GSHPs are highlighted, setting the requirements for GSHP control algorithms. The different approaches found in the literature to provide optimal control for GSHPs, with a special interest for the ones based on AI, are reviewed and classified, and their advantages and limitations are discussed. The latest advances in AI and how they have been used for HVAC or other building energy applications are reviewed and their relevance for GSHP control is disused. Constrains linked with their implementation on real buildings are also discussed.

The paper is structured as follows: Section 2 describes GSHP control's challenges. Section 3 reviews the different control algorithms found in the literature. Section 4 reviews the potential of further AI algorithms for GSHP operation. Section 5 discusses the challenges liked with the application of AI for GSHP controls and make recommendations regarding further research.

2. The challenges of GSHP control

A GSHP system can provide heating, cooling and domestic hot water with a single system and is more efficient than other alternatives [11]. A standalone GSHP system is composed of a Ground Heat Exchanger (GHE), a Heat Pump (HP), and a distribution system. There are different options for each of these elements (e.g. single vs. variable speed HP, single-U vs. double-U GHE, fan coil or radiant terminal units for distribution), resulting in a great variety of possible systems.

The HP is responsible for circulating the fluid in the ground and the distribution loops, and for transferring heat from the warmest side to the coldest. It is the main controllable element in a standalone GSHP system, together with the indoor temperature set-point. The Coefficient Of Performance (COP), representing the ratio of useful heating to the work provided, is used to characterise the HP's performance. For optimal operation, the number of times the HP is turned on and off needs to be limited to avoid accelerating the deterioration of the HP [12].

GSHP systems can be coupled with additional sources for heating (e.g. solar thermal collectors), for cooling (e.g. cooling towers-CT) or for both (e.g. air to water HP). Such systems are called Hybrid GSHP (HGSHP). They can enable to reduce the GHE size by reducing the peak load. HGSHPs are also useful to balance heating and cooling load to prevent long-term changes to the temperature of the ground [13,14]. HGSHPs have been demonstrated to reduce payback time [15,16]. Other elements such as thermal or electrical storage, or electrical generation systems (e.g. photovoltaic (PV) panel), can further improve the system. The optimisation of a standalone system is relatively straightforward, but with increased complexity of the system, the need for an optimised control strategy also increases. This is particularly true for HGSHP, where the load is shared between various elements.

The optimisation of a GSHP can be performed at the component level (local control), or at the system level (supervisory control), where the interaction between the elements is taken into consideration. A lot of work has been done at the component level [9,17] and in this paper, optimal functioning of the components will be assumed. The focus will be at the system level.

Because sizing is normally realised for the peak load, there is a need for control strategies that can deliver partial loads to achieve energy efficiency and comfort for the occupants. Operating costs is a third objective that need to be taken into account for the system's control optimisation. Finding the best equilibrium between those three objectives requires multi-parameter optimisation. In addition, control optimisation of complex GSHP systems is a non-linear and dynamic optimisation problem which tends to be more complex compared to more traditional HVAC systems.

Another element that needs to be taken into consideration is the long-term effect of the GSHP system on the ground. The heat injected and extracted should be adequately balanced to avoid ground thermal drift. According to Atam and Helsen, a lot of studies assume that the maximum capacity is provided by the geothermal component without considering the long-term performance [18]. To avoid exhausting the heat, two traditional hardware measures are usually considered: adding auxiliary heating or cooling systems, or over-sizing the system, which both increase operation costs. Alternatively a control system that optimise the use of the heat stored in the ground can reduce costs by reducing the length of borehole [19]. For commercial applications, where many boreholes are necessary to cover the demand, the interaction between the boreholes must also be considered [20]. Presence of ground water flow can further complicate the account of ground thermal behaviour [21].

The typologies of GSHP can vary greatly and the optimal control strategy will not always be the same, as it relies on the combination of several factors and variables. In addition, external factors such as weather and user preferences further influence the operation of the GSHP. Optimal GSHP control, thus, requires advanced and adaptable control algorithms.

3. State of the art of GSHPs control optimisation

This section reviews the research on GSHP control found in the literature. It first reviews traditional control strategies before looking at more complex optimisation techniques, identifying their strengths and limitations. A classification is proposed, and AI-based research is examined more in detail.

3.1. GSHP traditional control

The traditional way to control a GSHP is to turn the compressor of the HP on and off based on a temperature set-point, typically the return temperature of the distribution loop or the water tank temperature if there is one. A dead-band is defined around this set-point to prevent the HP from constantly turning on and off, and is coupled with an operation schedule. This type of control can be classified as a rule-based control. Rule-based control systems, also called Expert Rule Systems (ERS) [22], consist of a set of expert rules that trigger different actuations based on the system's state. They emulate the decision-making process of a human expert based on a set of *if-else* instructions. For HGSHP, these rules would orchestrate which heating or cooling source needs to be used under which conditions. Based on the approaches found in the literature, there are various possibilities to improve ERSs' efficiency: (1) Optimise the set-points, (2) Optimise schedules, (3) Optimise the parameter used for control, (4) Make more complex rules, (5) Adapt the architecture of the system.

The first strategy to improve ERS is to optimise the temperature set-point. For example, Corberan et al. studied the influence of the distribution loop parameters (set-point and bandwidth of room air temperature and distribution loop return water temperature) on the performance of the HP [23].

The second strategy is to improve the control schedule. This is especially relevant for HGSHPs where the auxiliary system is used to reload the ground. On an HGSHP with two CTs, Yang et al. studied the influence of different operating schedules on soil temperature, energy consumption, and operating costs. The strategies helped balance the heating and cooling load and reduced payback time [24]. Dai et al. carried a similar study for a solar-assisted GSHP comparing the influence of 6 different operation modes on the soil temperature recovery rate [25]. However, when compared to other strategies, Yavuzturk and Spitler found that fixed schedules performance is limited as it does not take advantage of weather conditions [15].

The third strategy to improve ERS is to identify the best control parameters. This strategy is especially relevant for HGSHPs where a high number of parameters is involved. Several studies have looked at the best control strategy for HGSHPs with CTs. When compared to other traditional rule-based control, Yavuzturk and Spitler [15], Sagia [26], Wan et al. [27] all found that strategies based on the wet-bulb temperature perform better as they best take advantage of weather conditions. Similarly, Gong et al. found fixed temperature difference between the cooling water leaving the HP and the ambient air dry-bulb temperature to provide the best COP and heat balance of the ground compared to more traditional control methods [28]. These four papers considered a fixed threshold for the control parameter.

Finally, control rules can be made more complex to improve system operation. Madani et al. compared floating hysteresis control, where the dead-band around the set-point is wider after a change of state of the system and gets smaller overtime, and the degree-minute strategy which considers the difference between the actual supply temperature and the required supply temperature over time, to the traditional set-point and dead-band strategy on a GSHP with an auxiliary heating system. The degree-minute method gives better results in terms of energy, as it better considers the dynamic of the building, when the floating hysteresis enables to stay closer to the desired temperature [29]. Emmi et al. proposed a decision tree between different operating mode for a solar-assisted GSHP based on the storage water tank temperature [30]. Different rules can also be combined to obtain better system performance. Based on a study of three buildings in different climates, Hackel and Pertzborn recommended rule based strategies to improve the operation of HGSHPs including (1) using pre-cooling in hot climate to cool the ground at night, (2) using HP bypass for small load management, (3) optimising set-points, and (4) including a warm up sequence [13]. Fan et al. found that combining traditional control strategies improved performance. However, the combinations that resulted in the lowest energy use and the one that best limited the heating of the ground over time were not the same [31].

To choose the best control strategy, Park et al. proposed a response surface method, a statistical regression method, to optimise the relation between GHE length and three rule-based control strategies: set-point control, differential temperature control and cool storage schedule control. The chosen design resulted in a slightly higher initial cost, but reduced energy consumption and net present value [32].

System improvement can also be considered at the design stage including elements with more control flexibility. To improve efficiency at partial loads, variable speed HPs can be used to perform variable capacity control. However, other aspects of the system should be considered: motor efficiency of the inverter and the compressor, and control of the pump [33], percentage of the peak load covered by the GSHP [34], trade-off between HP and system efficiency [35]. Multi-stage HP with more than one compressor and set-points to control when to switch them on can also be used to satisfy different building loads. At the system architecture level, there is also the possibility to have parallel or serial operation in HGSHPs. Cui et al. found fixed load ratio worked better for parallel operation while fixed entering temperature worked better for serial operation [36].

ERSs are commonly used in GSHP and HGSHP systems because they are easy to implement and to transfer between similar buildings, and they can be linked with design optimisation. However, the optimisation of the operation is likely to be minimal, as only a limited number of scenarios would be considered. In addition, as ERSs lack flexibility, the schedules and set-points tend to be conservative on the comfort side, leading to suboptimal operation. ERSs are also unlikely to adapt to long-term effect on the ground, leading to performance loss overtime. When systems become complex the ease of transfer and implementation might get lost. Finally, it is worth noting that rule-based control presented so far only works on the current state of the system.

3.2. Optimisation of GSHP control

Because of the limitations of ERS mentioned above, methods to improve GSHP controls have been investigated. This section proposes a classification of the different methods found in the literature and reviews traditional control optimisation methods.

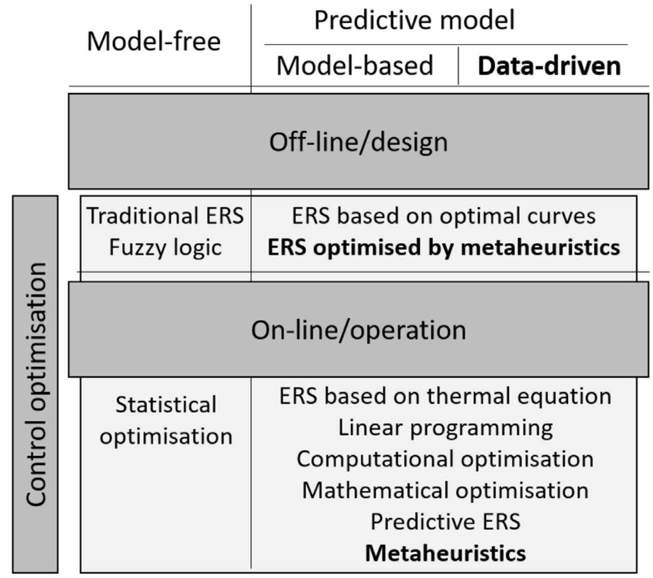

Fig. 1. Classification of GSHP control optimisation methods in the literature. Element linked with AI are in bold.

Supervisory control algorithms for GSHP are traditionally classified in three categories: model-based, model-free, and data-driven [6,18]. *Model-based* approaches use explicit knowledge to model the behaviour of the system. The model is then used to inform control decisions. Model-based methods give good results as they enable to generalise the behaviours of the system but can be expensive to implement.

In the *data-driven* approaches, the behaviour of the system is empirically modelled from performance data. Most of the data-driven approaches found in the literature are based on AI, although statistical analysis could also be used. Data-driven methods enable to account for the real behaviours of the system but obtaining good quality data is not straightforward and the model can only account for the behaviours observed in the training dataset.

Finally, the *model-free* approach consists in a control algorithm that is not based on a model. Although they tend to be classified separately, it can be argued that the rule-based systems are a subgroup of model-free approaches. Model-free algorithms have the advantage to be easier to implement but deliver lower system performance [18].

The classification presented above focuses on whether there is a model to predict the behaviour of the system and how this model is obtained (explicit knowledge vs. data). However, the strategy then used for decision-making also needs to be considered, as most control optimisation methods could be applied using either a data-driven or a physical model. Another distinction that need to be made is whether the optimisation is done once (e.g. during the design or commissioning phase) or if it is done continuously during operation. A classification considering both the type of predictive model and of control optimisation is proposed in Fig. 1.

Optimisations that are done once are done off-line, and are a direct evolution of rule-based systems. Fuzzy logic is a model-free approach that results in a qualitative expression of expert rules and improve on ERSs as it can handle uncertainty in the transition zones. An example of fuzzy logic applied to a GSHP and an HGSHP with a photovoltaic thermal (PVT) panel can be found in [37].

Another off-line approach is to optimise the relation between control parameters and relevant operating measurements. The resulting functions can then be implemented in a controller and be used in combination with traditional set-point controls. Del Col et al. used simulations, manufacturer information and experimental data to create lookup tables that maximise the COP of a GSHP system with variable speed pumps for different water supply temperatures [38]. De Ridder et al. used dynamic programming to obtain an array that determines the optimal flow from the GHE based on the field temperature, the demand, and the date to avoid the exhaustion of the ground heating/cooling capacity in an HGSHP [19]. Montagud et al. developed an in-situ optimisation methodology based on experimental measurements to optimise the circulation pump frequency for on/off operation as a function of the load [39]. The study was then extended to multi-stage circulation pumps [40] and to address some comfort limitations [41,42].

Off-line optimisations enable more complex strategies than ERS. They are still relatively easy to implement, as the results can be compatible with existing controllers. Another advantage is that they can be carried directly on design models. However, they still lack adaptability to the evolution of the performance of the system, and the parameters considered tend to still be limited.

To be able to take into account the real operating conditions of the system and the long-term changes in the boundary conditions, the optimisation can be done on-line and be embedded in the continuous operation of the GSHP.

A first approach is to use physical equations to include the thermal behaviour of the building as a metric in the decision process. These controls are still based on rules, but instead of making decision only on directly measured data, indicators about the thermal load are also considered [14,43]. Yang and Wang proposed a rule-based control to chose between operating modes of an HGSHP with a solar thermal collector using thermal balance equations to calculate the building load [14]. Hu et al. used the building load ratio for on/off control of a system with two HPs. Additionally, off-line optimisation is done on the HP flow rate using a global search method [43].

Another approach is to continuously optimise the set-points of the system. This can be done using linear programming, which consists in obtaining the best solution from a set of linear relations. Here a set of physical equations are used to calculate the best value for key control elements based on current measurements. Gao et al. optimised the set-point and the dead-band of the water return temperature in relation to the total energy consumption of the system for an Air Handling Unit (AHU) with GSHP as chilled water provider considering a maximum number of start-up of the GSHP per hour [12]. Edwards and Finn used design data and the compressor's on/off signal to optimise the water flow rate of the circulation pumps of a GSHP system at partial loads to maximise the system's performance [44]. de Paly et al. used linear programming, to optimise which GHE should fulfil the demand in a field of 25 boreholes and the long-term performance of the GSHP system [20,21]. Xia et al. combined linear programming with computational optimisation. A near-optimal performance map of the HPs was first generated to limit the search space. Then exhaustive search was used on a limited interval around the near optimal value. The different options were passed to a physical model. The feasibility of the settings was checked against measured values, and the solution that minimised the energy consumption was chosen [45,46].

Finally, Hu et al. proposed to optimise the control of a GSHP with a CT by using extremum seeking control. This method uses a mathematical model, instead of a model of the system's physics, where an objective function is minimised based on the control parameters. They used dither-demodularisation, a signal processing technique, to link inputs and outputs, which are the CT fan relative airflow rate and pump waterflow rate, and the power consumption respectively [47,48].

Those methods enable to improve the efficiency of the system compared to ERS, but are still *reactive systems*, meaning they use the current state of the system. However, because of thermal inertia of the building and intermittent production of renewable energy, further optimisation can be achieved by anticipating future states of the environment. This is commonly referred to as *predictive control*.

The most studied predictive controls are *Model Predictive Controls* (MPC). MPCs use mathematical models based on the physics of the system to predict its future states based on the boundary conditions. A control vector that minimises a cost function is generated over the time horizon considered. The first element of the control vector is applied to the system controls and the optimisation is carried out again for the next time step [49].

MPCs require a model based on a set of equations that can be optimised. These models need to be low order to make computation possible [50], which is non-trivial because the COP of the GSHP introduces non-linearity. Methods have been investigated to reduce the order of GSHP's models [51,52].

Several MPC approaches have been demonstrated on GSHP systems. Bianchi et al. demonstrated an MPC with pulse-width modulation on a laboratory test bed considering weather predictions and energy tariffs to optimise the load distribution during the day [53]. Antonov et al. compared short- and long-term optimisation for the MCP control of an HGSHP system [54] and proposed a method to address uncertainties [55]. Weeratunge et al. used an MPC with mixed integer linear programming to optimise the operation cost of a solar-assisted GSHP with thermal storage under dynamic pricing [56]. Atam et al. found non-linear MPC and a linear optimal control performed well [57].

MPCs give good results in terms of performances as the method can optimise multiple parameters of the system. However, they are costly to develop as they require adapted models. Therefore, the cost savings need to be significant enough to justify the implementation of an MPC.

3.3. *Artificial intelligence application for GSHP control*

The different approaches reviewed so far optimise GSHP control based on a trade-off between system performance and complexity of implementation. Due to the complexity of GSHP systems, there is a need for autonomous and adaptable intelligent controllers. The field of artificial intelligence has the potential to contribute to this goal. This section looks at the use of AI for GSHP control in the literature.

Zhou et al. reviewed the application of AI for GSHP and identified the following uses: building load forecasting, design data acquisition (soil thermal properties and ground temperature distribution), heat transfer property and design of GHE systems. When focusing on AI for GSHP control, this paper identifies three applications, which are reviewed in this section: (1) parameter optimisation; (2) system modelling; (3) control optimisation.

3.3.1. *Control parameter optimisation at design stage*

When investigating GSHP, a lot of work is traditionally done to find the best system design and AI has been used to optimise this process. There is also the possibility to consider the control parameters at this stage. Optimising control parameters can lead to reducing the length of GHE installed and thus the initial costs.

When considering many parameters, the computational cost of exploring the solutions systematically is prohibitive. A combinatorial optimisation can be performed using a metaheuristic optimisation algorithm [58] to explore the solution space faster, although a global optimal solution would not be guaranteed. Genetic and evolutionary algorithms are examples of metaheuristic algorithms suited for combinatorial optimisation. Genetic Algorithms (GA) are stochastic search algorithms inspired by population genetic selection [59]. They use crossover between the best individuals and random mutations to obtain better solutions until a stop condition is met (Fig. 2).

Zeng et al. used a multi-population GA to find the optimal solution for a hybrid combined cooling heating and power-GSHP system. The off-line optimisation, realised at the design stage, determined, along sizing parameters, the critical value for when to run the gas engine. This can be implemented in a ERS once the system is installed [60].

AI-based optimisation algorithms, like GA, enable to consider more parameters while performing design optimisation related to controls. The limitation of this type of optimisation, like any off-line optimisation, is their lack of adaptive capacity to the real operation of the system.

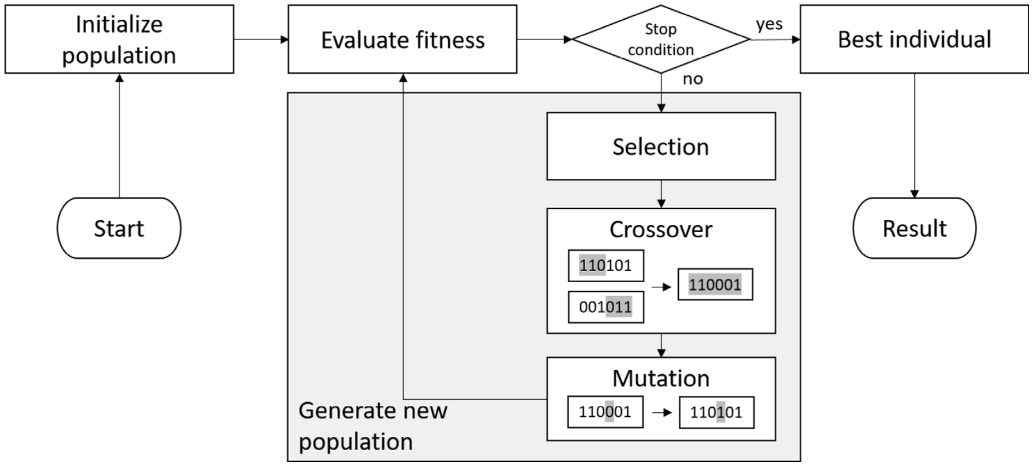

Fig. 2. Genetic algorithm principle.

The papers reviewed in the rest of this section address the operation phase of the GSHP life cycle, but since most of the research is based on simulated environments, in practice they could be devised at the design stage to ensure a good adequacy between the system components, their dimension and how they will be controlled.

3.3.2. Artificial intelligence for GSHP modelling

The predominant use of AI for GSHP control is to build data-driven models for predictive control. The development of physical models as described in 3.2, also called forward models, requires a detailed understanding of the physics of all the elements of the system and their interaction with each other. There is then a large number of parameters to determine. It can be done either based on manufacturers' data sheets, which can be imprecise as test conditions differ from operating ones, or with direct measurements, which increase the complexity of the forward model development. One further limitation is that some aspect cannot be predicted ahead accurately by forward models (e.g. solar radiation) [61]. In addition, forward models are often developed for design, which makes then too computationally intensive to use for operation. According to [62], forward models are useful for research or simple systems, but not practical for industrial exploitation.

By opposition, data-driven or inverse models are black-box empirical models that are obtained based on measured data and reflect the real behaviour of the system. The most used method for data-driven models are Artificial Neural Networks (ANN), which have the advantage of working well for non-linear models.

An ANN is composed of three different sections (Fig. 3): (1) the input layer, in which the ANN is fed with data; (2) the hidden layer(s), which contains N layers of varying numbers of neurons; (3) the output layer, consisting of a single layer with one or more neurons, produces the results. Each neuron represents a weight in a set of parametric equations meant to replicate the behaviour of a biological neuron. Non-linear activation functions are used to account for non-linearity in the observed data. The ANN is trained by using back-propagation based on the difference with the labelled data to update the weights of each neuron until they can satisfactorily predict the dataset.

Entchev et al. used ANNs to predict the indoor temperature at different time horizons. The prediction was based on the outdoor temperature, solar irradiance, and internal gains. This prediction was then used in a rule-based predictive control and was compared to a traditional on/off GSHP control. The benefit was clear for cost and energy, but there were some limitations on the comfort aspect [63].

Gang and Wang used an ANN to predict the supply temperature of the GHE and the CT of an HGSHP system. The two values can normally not be measured simultaneously as only one system is operating at any given time. An ERS was implemented based on the two predicted temperatures [64]. The approach was improved to limit on/off cycles of the HP. Over the four-year period simulated, the ANN predictive control provided better energy efficiency than traditional controls, although wet-bulb temperature difference control resulted in lower increase of the soil temperature [65].

Salque et al. implemented a predictive control strategy based on ANN models for weather prediction, borehole and radiant floor flow prediction, and room temperature prediction for a single-speed GSHP. When compared to conventional controls, the method resulted in increased comfort and significant energy savings [66].

Afram et al. used an ANN to model the different components of a residential GSHP system (Energy Recovery Ventilator, AHU, Buffer Tank, Radiant Floor Heating, GSHP). A Particle Swarm Optimisation (PSO) algorithm was then used to determine the set-points of the different elements that minimise operating cost with Time of Use energy pricing [62]. PSO is a metaheuristic algorithm, where the space of solutions is explored by assimilating the solutions to moving particles.

Because ANNs require large datasets to be adequately trained, alternatives have been investigated for when limited data is available. Esen et al. used an adaptive neuro-fuzzy inference system, hybridisation between ANN and fuzzy logic, to predicts the performance of a GSHP using only 38 inputs. The COP of the system was predicted based on the air temperature entering and leaving the condenser and the ground temperature [67,68]. The obtained model could be used for control decisions. The authors also used statistical weighted pre-processing, where the input values were transformed according to the training set average and standard deviation, to improve ANN training on the same case study [69].

Fang et al. used Gaussian Process Regression (GPR) to model power consumption and indoor environment from an experimental dataset. They were used to obtain control curves determining the optimal ventilation rate and supply water temperature from the compressor to optimise the predictive mean vote, the standard indicator for comfort, and power consumption of the GSHP [70]. GPR is a non-parametric Machine Learning (ML) method and was selected because it has been shown to outperform ANN for small data samples to obtain meta-models for design optimisation [71]. Fang et al. suggested the obtained curve could be used in ERS or MPC.

Data-driven models can consider the real operating condition of the GSHP system without the need to understand precisely every physical phenomena, as they are learned implicitly. They are also able to consider many parameters with non-linear relationship, leading to reduced modelling errors. However, it is not possible to generalise the output to conditions not observed in the training set and only measurable parameters can be predicted. The quality of a data-driven model is dictated by the quality and quantity of data available. A good model

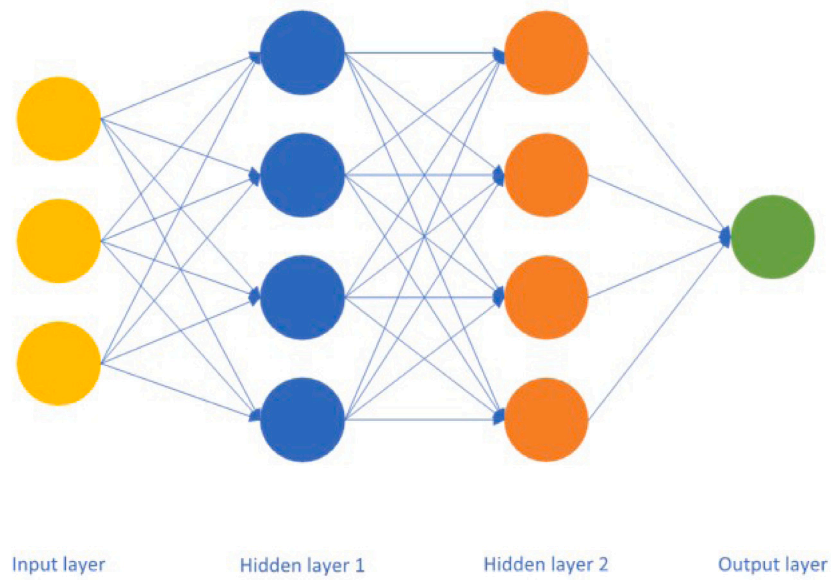

Fig. 3. Artificial Neural Network architecture: Multi-layer perceptron (MLP).

requires a dataset covering all the working conditions of the system. According to [18], high frequency data is also important to capture the dynamics of the system.

The most popular algorithm is the feedforward multi-layer perceptron (MLP) with one or two hidden layers, which is an ANN implementation. According to [72], ANNs outperform other black-box models, although for a small dataset, [71] found that GPR outperform ANN. In most cases, a different AI-based model is necessary for the heating and the cooling season [62].

Data-driven models cannot consider the long-term effect on the GHE, as it would be unlikely to have access to 20–30 years of data [18]. However, they can be adaptive, meaning the model can be re-calibrated with recent data, thus adapt to changes in the system or the environment.

3.3.3. *Artificial intelligence for control optimisation*

As demonstrated in the previous section, AI can be used to make predictive models. AI can also intervene to optimise the control decision for predictive control. When control actions need to be optimised on a given time horizon based on future conditions, control optimisation can be assimilated to a combinatorial problem and solved by metaheuristic algorithms similarly to Section 3.3.1. Evaluation of the solution is made using a predictive model of the system.

As a step further to model-based control optimisation, Xia et al. used simplified adaptive models that were updated in real time with the recursive least square method with exponential forgetting combined together with a GA to find the optimal control solution for a hybrid GSHP system with a PVT collector [73].

Ikeda et al. used an epsilon-constrained differential evolution (DE) with random jumping to provide a 24h-ahead operating schedule for an HGSHP, taking into account ground thermal history and optimal load dispatch between the different sources of the system [74]. Like GA, DE are evolutionary algorithm, but the new solutions are generated based on vector differences.

Metaheuristic optimisation enables to consider large solution spaces without systematic exploration, making real time optimisation possible. In [73,74], the models used were forward models, but similar methods could be applied using data-driven models like in [62].

Mokhtar et al. used an ARTMAP for control decisions within a multi-agent system controlling a GSHP and a boiler [8]. ARTMAP is a supervised ANN belonging to the adaptive resonance theory family [75]. Here, ARTMAP is used to group the measured data into clusters that are then used to make control decisions. The authors do not describe how the training data are obtained which does not permit to assess how optimised the control decisions are.

In this section, the different approaches to tackle the optimisation of a GSHP or HGSHP system's control have been presented. The control of the system is either optimised during the design phase or the operational phase. The former ensures that the design will produce a control system capable of leveraging the different installed elements at optimal performance. The latter ensures that the management of the devices will reduce the energy consumption by considering current or future external variables (e.g. energy demand, weather). Table 1 classifies the papers reviewed in this section based on Fig. 1. Model-free methods are mostly for off-line optimisation and until now the use of AI for GSHP control has focused mainly on producing predictive models. The use of AI for control optimisation is limited to date, although it was demonstrated that metaheuristic algorithms can give good results.

4. Opportunities of Machine Learning (ML) for GSHP control

As demonstrated in the previous section, AI has potential to improve GSHP control, but only a few among the vast array of techniques have been tried to date. Traditional ERSs as presented in 3.1, which are the first step of intelligent decision-making systems, require expert knowledge and can become limited or suboptimal for complex systems. Ruelens et al. demonstrated their limitation when using an ERS to overrule the ML control of the thermostat of a HP [76]. ML is a category of AI which enables to gain knowledge automatically through the use of data. ML algorithms are a promising approach to overcome limitations of ERS systems and they can also complement model-based approach by their ability to consider non-modellable parameters such as occupancy or weather. Those aspects are key to predict demand and RES production, as well as optimising the relation between energy efficiency and comfort.

In this section, different ML based approaches will be reviewed with the aim to identify how they can benefit GSHP control. First transitional ML algorithms are presented before moving to Deep Learning and Deep Reinforcement Learning.

Table 1
Classification of GSHP control research. MF: Model-free, MB: Model-based, DD: Data-driven. (*) indicate the use AI.

Predictive control			Control optimisation	Pros	Cons	Ref	Year
MF	MB	DD					
			Off-line				
x			ERS	Easy implementation	Suboptimal operation	[13,15,23–36]	2000–2018
x			Fuzzy logic	Accounts for uncertainties	Intermediary performance	[37]	2015
	x		ERS + metaheuristic*	More configurations tested	None-adaptive control	[60]*	2015
	x		ERS based on optimal curves	Compatible with traditional controllers	Non-predictive control	[19,38–42]	2011–2017
		x*				[70]*	2018
			On-line				
x			Extremum seeking control	No forward model needed	No account for building physics	[47,48]	2014
	x		ERS based on thermal equation	Accounts for building load	Non-predictive control	[14,43]	2012–2017
	x		Linear programming	Optimal solution from equations	Requires simple equations	[12,20,21,44–46]	2012–2017
	x		Mathematical optimisation	Good performance	Costly to implement	[51–57]	2013–2018
		x*	Predictive ERS	Predictive control based on real performance	Requires a good quality dataset	[63–69]*	2008–2013
	x		Metaheuristic*	Good solution considering future state	Might not find the global optimal solution	[73,74]*	2017–2018
		x*				[62]*	2017

4.1. Traditional Machine Learning algorithms

ML algorithms are based on mathematical formulas which are optimised by performing a training process using a set of data. There are different ML-based algorithms suitable for different tasks. ML algorithms are commonly classified into three groups: (1) *supervised* classification, in which a labelled training dataset allows the algorithm to learn how to label new observations; (2) *unsupervised* classification, in which the given dataset is not labelled and the algorithms try to group the data using its properties and latent relationships; (3) *reinforcement learning* in which an agent learns based on a system of rewards. Table 2 lists a sample of common ML-based algorithms and the kind of task they accomplish. Those algorithms have been used extensively in the literature and are the foundation for more cutting-edge ML. These algorithms require a *feature engineering* process. Feature engineering consists in selecting the most meaningful properties from a raw data source based on expert knowledge and statistical analysis.

The papers using ML identified in Section 3.3 are mostly based on supervised neural networks, although a few also use regression techniques, and were used to generate predictive models. When looking more generally at the HVAC control field, AI uses focus on building load forecasting, and prediction of system consumption, indoor thermal comfort, and air quality [88] and the most common optimisation techniques used are stochastic gradient decent, genetic algorithms and global convergence algorithms [89]. In a review of data-driven approaches for building load forecasting, Ahmad et al. classified the existing approaches as ANN-based, clustering-based, statistical and ML-based, and Support Vector Machine (SVM)-based [90].

In addition to the generation of predictive models of the behaviours of the system, ML learning can be used to predict the energy demand of the building, which is important for short-term optimisation of GSHPs. This has been investigated in several studies.

For example, Robinson et al. used ML algorithms to predict the energy consumption in commercial buildings. They used a dataset extracted from a survey performed by the U.S. Energy Information Administration. Using this information, they demonstrated that gradient boosting algorithms outperformed other types of supervised based ML algorithms such as Random Forest (RF), Linear Regression or KNN in the process of estimate the commercial building energy consumption [91].

Edwards et al. trained seven different supervised ML algorithms and determined which techniques were the most successful at predicting energy consumption for three residential buildings located in west Know Country, Tennessee. To do so, they used a residential dataset which contained 140 different sensors measurements collected every 15 min. They compared prior studies around traditional energy modelling (model-based) by using expert knowledge versus the sensor-based modelling process (data-driven). They found that Least Square SVM was the best ML algorithm for energy prediction [92].

Yang et al. proposed a data-mining-based approach to predict the energy consumption of a chiller. They applied different ML algorithms on a dataset containing energy consumption, weather data and the building operation processes. There were some limitations because the proposed method lacked the ability to deal with noisy data. To solve it, they identified and removed this data, but the process is not optimal and requires further research. They concluded that non-linear model gave accurate results for predicting energy consumption [93].

Kontes et al. proposed a novel methodology in which they created an intelligent building energy management system using the model of a Greek building. They trained a SVM algorithm by using the simulation environment Energy Plus to obtain reliable information on the building consumption and its thermal behaviour over the time. With the trained algorithm, they obtained around 35%–57% of energy saving in comparison to the default rule-based strategy [94].

Pham et al. used a data-driven approach combining five different datasets to predict hourly energy consumption in different time windows. They trained ML models to evaluate the energy consumption prediction accuracy 1, 12 and 24 h ahead. In this study, RF outperformed the other types of algorithms used [95].

Culaba et al. used ML algorithms for the energy consumption prediction of mixed-use buildings. Based on simulations, they created a dataset from 30 hypothetical mixed-use buildings (model-based). The dataset was used to perform a clusterization using K-means algorithms, which allowed to explore similarities in the energy consumption of different mixed-use buildings. A SVM algorithm was then used to forecast the energy consumption within each cluster. They used real weather data (data-driven) to predict the weather [96].

There are different traditional ML algorithms that can be used to predict the energy consumption of a building. This is a useful parameter to consider when controlling a GSHP, as it enables to implicitly include occupancy and weather as a control parameter. ML models enhance the usage of the real data acquired from different sensors and allow the creation of intelligent agents to perform actions if needed or simply provide information to understand what the energy requirements of a building are. Control strategies can then use the energy demand for decision-making.

4.2. Deep learning

Building on traditional ML algorithms, Deep Learning (DL) is an approach that works on big datasets and reduces the need for feature engineering. It is particularly efficient at finding hidden relationships between the data.

Table 2
Traditional ML algorithms. S: Supervised, NS: Non Supervised, RL: Reinforcement Learning.

Type	Name	Description
S	Linear Regression [77]	A line which fits two or more properties.
S	Random Forest (RF) [78]	A randomised decisions tree.
S	XGBoost [79]	A eXtreme Gradient boosted decision trees.
S	KNN [80]	K-Nearest Neighbours, a classification using the nearest properties.
S	Support Vector Machine (SVM) [81]	Draws a virtual line which divides the data in different groups.
S	Neuronal Networks [82]	Networks composed by digital neurons which emulates the brain.
NS	K-Means [83]	Similar to KNN but it create clusters using the mean of the properties.
NS	Hclust [84]	Hierarchical clustering process to create a tree of properties.
RL	Q-Learning [85]	A *model free* algorithm based on Temporal-Difference RL.
RL	Monte-Carlo [86]	A *model free* algorithm which learns from complete episodes.
RL	Bellman expectation equation [87]	Policy discovery equation for fully observable environments.
RL	Bellman optimally equation [87]	Policy improvement equation for fully observable environments.

Inside classical ML algorithms, the Multi-Layer Perceptron (MLP) is the base for ANN architecture as described in Section 3.3. The MLP demands high computational power which has limited its use until recent years when improvement in the hardware has made possible the training of very deep neuronal networks with many hidden layers and neurons in a reasonable time. These very deep MLPs are known as Deep Learning [97]. The main difference with traditional ANN is the increased number of hidden layers. This then gives way to more complex architectures like Convolutional Neural Networks (CNN), Recursive Neural Networks (RNN) or autoencoders, which are able to solve increasingly complex tasks.

When looking at applications of DL for building energy management, various studies have shown that DL provides improved prediction capacity compared to traditional ML. For example, Fan et al. used DL-based algorithms to perform a load prediction of a cooling system using data of an educational building in Hong Kong. They used two types of datasets to train their models: the first contained data from the previous 24h and the second only considered measurements from the previous hour. They trained seven different algorithms and demonstrated that the DL approach outperforms the rest of the ML-based algorithms used [98].

Marino et al. used Long Short-Term Memory (LSTM), an RNN architecture, to build an energy load forecasting algorithm to perform building level load forecasting [99].

Cai et al., presented a comparison between different time-series DL models based on RNN (like GRNN1, GRNN2), or based on CNN (like GCNN24); and between classical time-series algorithms like SARIMAX and showed DL algorithms to perform better [100].

Son et al. used DL to forecast the energy production of a PV panel. They compared their baseline algorithms, which relied on active sensors installed in the PV panels, against a DL-based approach, using only the PV output history and the local weather forecast historical data. With only one year of training data, they obtained slightly better results than their previous approaches suggesting that DL is suitable for fine-tuning the problem of PV output power forecasting [101].

Zhang et al. used a hybrid approach in which they used LSTM networks and ANN algorithms to extract features from time-series data to predict the energy loads of a target building. To train the proposed method, they used a public dataset of a building located in Shenzhen, China. In addition, they compared four different algorithms (Support Vector Regression, ANN, RF and Gradient Boosting trees). To evaluate the performance of each proposed algorithm, they used the load data and the outdoor meteorological data of the building to predict the hourly cooling loads of the target building [102].

Li et al. combined Stacked Autoencoders and Extreme Learning Machine in a DL algorithm to obtain accurate energy consumption prediction of a building. In order to ensure that their approach outperformed the state of the art, they compared it with different traditional ML algorithms such as Support Vector Regression, Multiple Linear Regressions and Back propagation ANN. They used a partial auto-correlation function to select the most sensitive input variables to use in the training procedure and to train their algorithms, they used a public dataset containing samples collected every 15 minutes from a retail building in Fremont, CA [103].

Mocanu et al. used DL to estimate the building energy consumption using an individual household electric power consumption dataset from UCI Machine Learning repository. They compared different algorithms and demonstrated that the used DL-based algorithms (Conditional Restricted Boltzmann Machines and Factored Conditional Restricted Boltzmann Machine) outperforms the results obtained by ANN, SVM or RNN [104].

Based on the good results DL shows for predictive task, it has the potential to improve data-driven predictive models for GSHP control and other relevant predictive tasks like load forecasting. The main disadvantage of DL is the requirement of a large dataset so that the different weight of the ANN can be trained accurately and without overfitting, but it has the advantage to limit the feature engineering as bias in the data can be learned implicitly.

4.3. Deep Reinforcement Learning

The applications of DL reviewed in the previous section are focused on predictive models. Those are useful to improve the control decision-making, but normally require additional rules or optimisation process. This section focuses on RL, a family of algorithms which acts directly on the decision-making process and can optimise control strategies in the case of GSHP control.

Reinforcement Learning (RL) is a set of ML based algorithms which emulate the psychological concept of learning by giving positive or negative rewards to reinforce an action or a set of actions. The concept of RL appeared in the literature in neurological studies on animals in [105] which studied their behavioural changes by doing different error-testing experiments. At the neurological level, it was demonstrated how the reinforcement rewards changed the structure of the neurons, and consequently, the decisions and actions of the subject [106].

Bellman created the first mathematical formulation of a RL problem, using the concept of Markov Decision Processes (MDP) [107]. These processes are mathematical models which are represented by states and actions that a human being could perform following a decision-making neuropsychological process where the results are uncertain [108]. MDP modelling was subsequently used to develop different algorithms and try to optimise the MDP process. Some well-known algorithms in the literature are Dynamic Programming [87] and Linear programming (Q-learning [85], or Monte Carlo [86]). Sutton and Barto developed the first formalisation of the concept of RL in machine learning [109].

Fig. 4 depicts the MDP process followed by a RL agent. The agent's timestamp is represented by the time step (t). The agent's perception of the target environment at time step t is defined by the state (S_t). The agent selects an action (A_t) to modify its environment. The environment returns to the agent a new State (S_{t+1}) and a scalar value called Reward (R_t) which identifies how good or bad the action was. The objective of the agent is to maximise the cumulative reward over time.

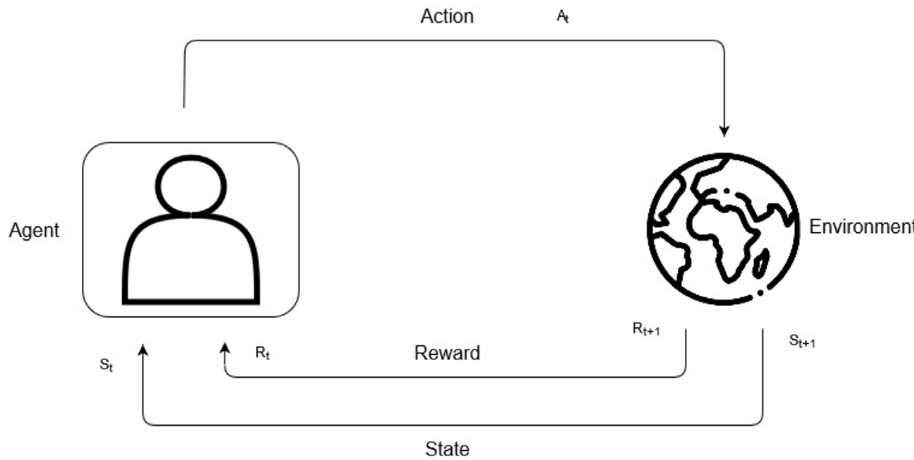

Fig. 4. Reinforcement Learning schematics.

Table 3
Different DRL-based algorithms.

Name	Action state	Type
Deep Q-Learning	Discrete	TD-Learning
Double Q-Network	Discrete	TD-Learning
Dueling Network Architecture	Discrete	TD-Learning
Advantage Actor–Critic (A2C)	Continual	Actor–Critic
Asynchronous Advantage Actor–Critic (A3C)	Continual	Actor–Critic
Soft Actor–Critic	Continual	Actor–Critic
Proximal Policy Optimisation	Continual	Policy Gradient
Deep Deterministic policy gradient	Continual	Policy Gradient
Trust Region Policy Optimisation	Continual	Policy Gradient

The concept of *Deep Reinforcement Learning* (DRL) appeared in the literature when Mnih et al. developed a variation of the Q-Learning algorithm called DQN. The decision-making agent was substituted by a Deep Neuronal Network, which receives the current states of the agent as an input, and predicts the value of the different actions possible. This enables to account for a greater number of state–action pairs [110].

Fig. 5 illustrates the DRL approach. A neuronal network receives the current state (S_t) and outputs a valid action (A_t) to perform in the environment. The rewards (R_t) from the environment are used to update the internal weights of the neuronal network, which represents the policy π of the agent. These weights are updated interactively using a stochastic gradient descent following a custom loss equation. This approach, where the agent learns a policy π by iterating over the environment and updating its weights, is being used extensively in the literature. The main advantage of using a neuronal network as an agent is the capacity of DL-based networks to find latent relationships between the state space and the value of the actions to maximise the agent's reward. Nevertheless, the developed DRL algorithms have some disadvantages. For example, they add a layer of complexity to the traditional RL methods because a neuronal network must be implemented. In addition, the DRL approaches sometimes lack the capacity to learn how to perform a specific task unless they have prior knowledge.

Table 3 lists different DRL-based algorithms. The algorithms are organised based on: (1) whether the action state is discrete or continuous; (2) the type of the algorithm which can be Temporal-Difference, Actor–Critic and Policy Gradient.

Brandi et al. trained a DRL agent to control the supply water temperature of heating terminal units. The terminal units were modelled using EnergyPlus. The developed agent selected the supplied water temperature by configuring the set-point taking into account discrete actions from the action space $A_t = \{20, 40, 50, 60, 70\}$ [111].

Liu et al. used DRL to make short-term energy consumption predictions of the energy required by a GSHP system. They captured real data from the GSHP and used the information of the local weather station to create a first raw dataset. Then, they used autoencoders to perform a feature extraction in which a final training/testing set was created to make a high-dimensional representation of the agent states. The agent was then trained and its actions represented the short-term energy consumption of the GSHP [112].

Yang et al. used RL agents trained on a Simulink model to control an HGSHP system with PVT panels. They first used a RL controller for the PVT system, leading to an increase in performance of 10% compared to the rule-based alternative after 3 years. Then, to control the whole system, they added a similar RL controller to the GSHP loop and the distribution loop demonstrating improvement of all the control objectives compared to the rule-based solution [113].

DRL is capable of solving different tasks for HVAC control, either predictive, or, more interestingly, by directly learning optimal control strategies via trial and error. The initial studies for GSHPs are promising, but more investigation is needed.

The use of a simulation environment (e.g. EnergyPlus, Simulink) is crucial to test DRL agents and understand how they train. These simulation environments ensure the acquisition of useful training data without noise caused by unexpected external factors. They also allow to test the performance of the trained agents in the long run by creating different scenarios to test how they affect the behaviour of the trained DRL models.

However, there is a gap between how a DRL agent behaves on a real environment compared to the virtual training environment. In this regard, comparison is needed between the trained agents in virtual environments against the results obtained when they are executed on a real system. Data is needed to understand how a DRL based agent is capable of modifying its behaviour and adapt its internal policy to the variations not considered in the virtual environment.

5. Discussion

The literature shows the relevance of optimising GSHP controls to reduce costs and increase energy efficiency, which in turn can facilitate a greater market penetration of geothermal energy. Artificial intelligence (AI) shows potential for two key aspects of this optimisation. On the one hand, to create data-driven models that can predict the real, short-term performance of systems as a basis for control decision. On the other hand, to optimise the control decision themselves. Based on the different fields of artificial intelligence, other method could be explored to further optimise GSHP operation. In this section, the challenges that need to be overcome to improve and implement those systems are discussed.

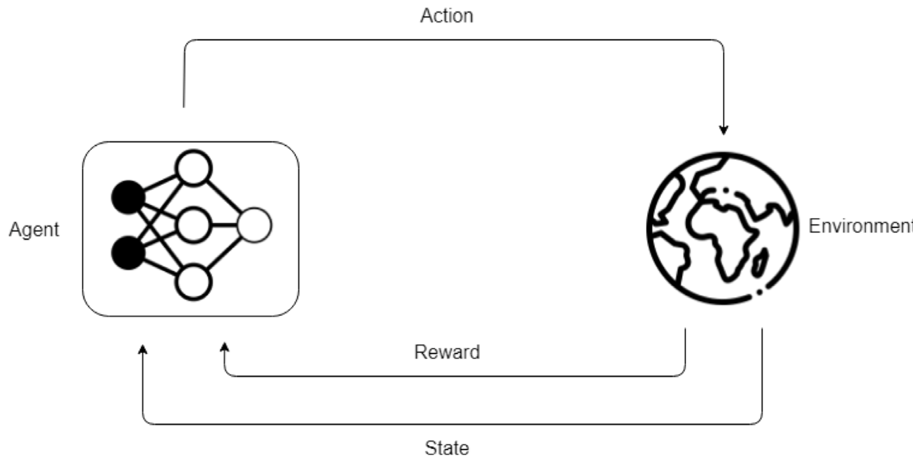

Fig. 5. Deep Reinforcement Learning schematics.

5.1. Challenges of GSHP control optimisation reporting

As it is often the case with building system research, the studies carried out for GSHPs are specific to a case study. Those case studies have value because they enable to test hypotheses, generate knowledge and their findings can be extended to similar cases. However, if rule-based conclusion can be easily transferred to new cases, the more complex the control, the more variation will happen between cases and comparison of results becomes difficult. This leads to a series of techniques to be developed in parallel without a clear view of which perform better for which typology of GSHP system. In the literature, common typologies emerge. Standalone GSHP, hybrid GSHP with CTs, and hybrid GSHP with PV or PVT are the most common ones. Although their exact set up differs, defining archetypes based on these technologies would permit more consistent research. It would also permit researchers to focus on the control optimisation, without having to define a use case from scratch.

In addition to being system specific, studies are also specific to the defined environment (e.g. weather, soil type). When the study is done on a real case it is inevitable, but when simulation is used, comparison between different environments would be interesting to better understand how they influence the performance of the control algorithms in order to better generalise them. Although the choice of system architecture will depend on weather conditions (cooling dominant, heating dominant, moderate climate), there will still be variations within these broad climate groups that affect the outcome (e.g. humidity of the climate, peak temperatures).

To benchmark different control strategies, it is also important to have results relative to different optimisation objectives. Some studies focus on energy (e.g. [73]) other on operating cost (e.g. [62]) and data are missing in the other aspect to evaluate the trade-off. Another key element for a successfully control algorithm is how it affects the comfort of the occupants, which few of the reviewed papers assessed.

It is also important to look at the long-term performance of the proposed control algorithms. A lot of studies focus either on cooling or heating, thus not considering the full-year performance and even fewer studies look at performances beyond a year, unless the main objective of the study is to compensate for load imbalance.

Most of the studies reviewed are using a detailed model of the system to test the performance of the control strategies. In some studies, the model is validated with real data (e.g. [12,28]), bringing the study closer to a real case. Bianchi et al. conducted their research on a laboratory HP test bed, which enabled them to test and control various operating scenarios. Real world validation requires access to real systems and the ability to control them, which is not easily obtained, but in case studies based on simulations, some real-world factors might be neglected, making wide implementation difficult.

Having well-defined archetype cases for GSHP control would permit comparability and also accounting for more aspects relevant to the development of robust and advanced GSHP control algorithms. The ideal scenario is for those archetypes to be linked with real cases, so that the algorithms could be validated in real conditions.

Additionally, to properly evaluate the impact and feasibility of innovative control strategies based on artificial intelligence techniques and adequate comparison between them, a common methodology of reporting results is necessary. The literature often only reports on the metrics linked to energy/cost, but is missing detail about the AI algorithm metrics such as training time or GPU use, which is especially relevant to evaluate the trade-off between energy saved by improved operation and energy used for ML training. In most cases, key elements are lacking to understand how the AI was implemented, as information is missing regarding the formalisation of the model, the training set or the hyperparameters used, which prevents replicability of the investigation.

5.2. Challenges of physical implementation

The application of the discussed AI algorithms and control strategies in a real-life scenario requires the acquisition of real-time information on the status of the system, the building or climate conditions, a GSHP that can be controlled automatically, and a management system capable of applying the control strategies defined according to the current conditions and of sending the corresponding commands to the GSHP.

Smart Buildings are complex ecosystems that traditionally comprise sets of sensors that capture the state of the environment; management systems that analyse the information provided by the sensors and decide the actions to take; actuators that allow the control of the facilities; and interfaces for the owners or managers of the building to be able to monitor or take control of the system.

Traditionally, these systems have followed a centralised *architecture*, with a central manager that handles all the information generated and sends the corresponding commands, either locally or in the cloud. The evolution of the ICT technologies has improved Smart Buildings, adding new features and capabilities. It is the case of *IoT networks*, which allow real-time monitoring and control of the facilities and have brought the capacity to integrate more elements to the system. The increase of available data (in quantity and heterogeneity) permits the development of more accurate and complex control algorithms, including the integration of AI algorithms. However, its processing is much heavier and less manageable and has brought the need to rethink the Smart Building architecture [114,115]. Edge and fog technologies bring the computing capabilities closer to the sensor. All the data captured does not travel to a central management system, but it is, at least partially, processed in a node close to the sensor network. This allows the scaleability of the solutions, as well as the management of great amounts of data, it increases the security and reduces the latency of the systems.

Beside its substantial volume, data handled in this smart building environment is also highly *heterogeneous*. An optimal GSHP control requires taking into account energy needs, user comfort and varying energy costs. Thus, information regarding the physics of the building (e.g. size, distribution, insulation level or heater types) must be combined with the IoT networks and the multiplicity of their types of devices (e.g. water or air temperature sensors, consumption meters of the GSHP) and with external sources (e.g. weather forecast, energy prices). For smart systems to automatically handle data, they must have a consistent way to represent all the information, regardless of its source, and must also understand the nature of each piece of information and what every value represents. Gilani et al. reviewed different technologies to deal with these challenges: semantic web technologies, which are often used for allowing cross-domain interoperability, and ontologies, that support data readability and machine reasoning, defining concepts that allow the interpretation of data [116].

Apart from understanding the data, it needs to be trusted. All the knowledge extracted and the decisions taken by the AI algorithms for the GSHP control are based on the data obtained automatically, with no human supervision, from an IoT network which is subject to errors due to sensor battery losses, device malfunctioning, noise or communication losses. Therefore, *data quality* must be ensured, since low data quality will result in unsound decisions and poor GSHP performance. A review on how these data quality problems manifest themselves in IoT networks (roughly grouped in two classes: dropped readings, which result in the loss of data, and unreliable readings which result in the reception of erroneous data), and on the data science techniques that can be applied to avoid them can be found in [117].

Last, since the IoT network is usually connected to the Internet either directly or indirectly, serious concerns regarding the *security and privacy* of the occupants arise. This issue is even more pressing in an environment where cloud, edge and fog architectures are progressively becoming predominant, in part to allow the deployment of AI algorithms. The information from sensors, especially those that could lead to knowledge on the occupants' activities, such as the energy meters, should only be accessed by authorised elements; the identity of the devices that send commands to the GSHP or of the external sources of information such as weather or energy cost servers should be guaranteed; and, in general, the performance of the system under different well-known attacks should be ensured [114].

The research community has generated a great amount of knowledge about the energy efficient operation of systems like GSHP, but to achieve significant CO_2 reduction in building, there need to be a generalisation of this knowledge. It would be cost prohibitive for an energy expert to perform a detailed study of each and every building to determine its optimal operating conditions. This is why building energy expert and information technology experts need to work hand in hand to achieve energy efficiency.

6. Conclusions

This paper reviews the state of the art of GSHP control and the potential of Artificial Intelligence to reduce operating cost and improve energy efficiency. Distinction has been made between methods that are applied off-line and can be implemented at the design stage and the ones that are done continuously during operation. Those control methods can be model-free or based on a predictive model. Predictive models can either be based on physical laws or inferred from a dataset. GSHPs are complex system and thus require controls that can adapt to their operating environment so that maximum performance can be achieved, making online optimisation better adapted for their control. These controls need to account for real operating condition of the HP, variation in external condition such as weather and demand, and long-term variations of the systems' performance.

The field of Artificial Intelligence provides algorithms that can learn complex patterns from data and work with a great number of parameters without the need of explicit knowledge to link them. These algorithms can provide autonomous and adaptive control to better control GSHP for energy, comfort and cost optimisation, but long-term performance need to be better included in their learning objectives. The focus in the literature so far has been on using AI to build predictive models of GSHP systems. The progress on deep learning could further improve predictive tasks when large datasets are available. Regarding control optimisation, examples of artificial intelligence applied to GSHPs has been limited to date. Metaheuristic algorithms have been used with success and progress in the field of deep reinforcement learning are promising, but further research is needed to streamlin the transition between virtual and real environments.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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