Application of Machine Learning in Energy Systems – a Comparative Analysis of Three Case Studies

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Abstract:
The exponential growth in the number of papers published annually in the field of machine learning applications in energy systems presents a challenge to researchers seeking to conduct comprehensive and effective literature reviews. To address this issue, we took a systematic literature review approach with three distinct smaller case studies focusing on the application of machine learning in energy systems, namely:

1. Machine learning in drilling
2. Machine learning for rooftop solar energy potential quantification, and
3. Machine learning in district heating and cooling in the context of seasonal thermal energy storages.

In each case, we employed a systematic literature review methodology. For topic one, we utilized an existing comprehensive review to generate further insights and information. For topics two and three, we used predefined search criteria to conduct relevant publications in a systematic and reproducible manner. We investigate the state of the art of the use of machine learning in these distinct areas of inquiry, thereby facilitating the identification of research gaps. Ultimately, we compare approaches and models utilized in each field, identified common best practices, and propose methods to address potential challenges.

Keywords:
Energy systems, Machine Learning, Drilling, ATES, Roof Potential, Geothermal, Aerial Imaging, Renewable Energy, District heating and cooling, Seasonal Thermal Energy Storage

1. Introduction

Energy systems are the backbone of modern civilization and are critical to promoting environmental, economic, and social sustainability [1]. As energy systems become increasingly complex, they require higher reliability demands and offer greater degrees of freedom for practical enhancement of integrated multi-energy systems [2]. Machine learning-based data-driven models have emerged as a promising approach for significantly improving the overall usage rate of multiple energy sources, especially including renewable energies [3]. Machine learning can capture complicated mechanisms to increase prediction accuracy, make optimal choices based on detailed state information, and reduce computational time needed for energy system optimization [4, 5]. In addition, machine learning has been applied to develop advanced energy storage devices and systems [6]. In this review, we explore three impactful applications of machine learning in energy systems and the challenges and limitations that must be addressed for further progress in this field.

Case Study Approach

We adopt a systematic literature review approach to investigate the state-of-the-art in application of machine learning by conducting three distinct case studies. The aim is to provide valuable insights into the potential of machine learning to solve complex problems across different fields. In the first case study, an analysis of a recent review paper on machine learning in drilling by Li et al. 2022 [7] is conducted to provide additional insights. The second case study focuses on the use of machine learning in rooftop solar energy quantification, while the third case study examines the use of machine learning in district heating and cooling in the context of seasonal thermal energy storages. These case studies showcase the application of machine learning in different sectors, such as load demand forecasting, design, cost, and control optimization. The specific machine learning techniques used, challenges faced, and an outlook in each field are presented. By exploring these case studies, this review paper aims to provide a comprehensive understanding of the state-of-the-art in the application of machine learning and its potential for solving complex problems in various fields. After introducing the applied methodology for each case study and the subsequently chosen selection of papers,

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we provide in the results section for each case study a case study results subsection followed by a short case study conclusion and outlook. We conclude with a summarizing conclusion and outlook across the case studies.

2. Methodology

Organizing and planning literature searches is a complex process that requires careful attention to several key categories. These include defining the scope of the literature, conceptualizing the topic, conducting a literature analysis, searching for relevant literature, and developing a research agenda. Various search processes have been introduced to enhance the quality of literature reviews, such as journal and database searches, keyword searches, backward and forward searches, and evaluation of the title and abstract of relevant literature [8]. To ensure effective literature searches, it is also recommended to gain a thorough understanding of the subject matter, test and apply a combination of search parameters, and use seminal sources to build the backbone of the literature review [9]. Our paper employs the Concept Matrix Method [10], which is aligned with these guidelines to ensure accurate and efficient collection, study, and categorization of the survey. In our case studies, we use relevant keywords to conduct literature searches on Google Scholar.

The first case study focuses on machine learning in drilling, which is an enormously active research field. As one can see in Figure 1, the number of papers published per year on machine learning in drilling shows an exponential increase. A very recent and comprehensive review of Li et al.2022 [11] will here be our base of research, whose content we will analyze further in the following.

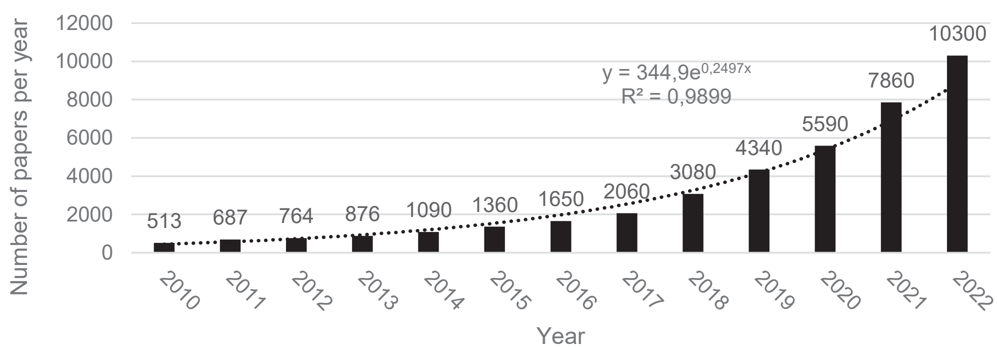

Figure 1: Number of papers published for per year when searching for “machine learning” + “drilling” showing an exponential increase.

The second case study explored the field of solar rooftop potential quantification by finally narrowing down to the search string "machine learning" + "solar energy" + "rooftop" + “quantification” + “urban” + "aerial image" + "geographic information system" (cf. Figure 2).

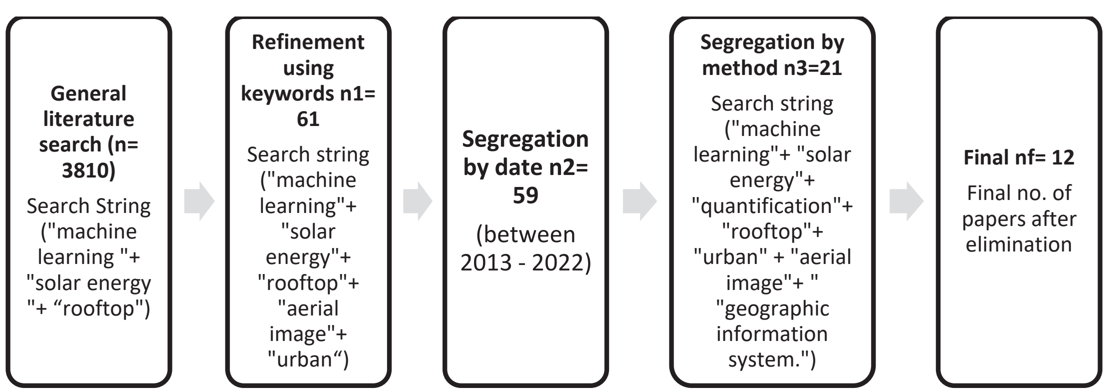

Figure 2: Steps involved in the refinement process for the case of solar rooftop potential quantification using machine learning.

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The systematic literature search was undertaken in Google Scholar. Using the search string "machine learning "+ "solar energy "+ “rooftop yielded 3810 papers. The number of results was then reduced by inserting the term "urban" and “aerial image” to the search string to 61, resulting in the search string "machine learning"+ "solar energy"+ "rooftop"+ "aerial image"+ "urban". The results were narrowed down to 59 by excluding publications published on or before 2012. Adding the term "geographic information system" decreased the results to 21 for the search string "machine learning"+ "solar energy"+ "rooftop"+ “quantification” + "urban" + "aerial image"+ "geographic information system", which then where finally reduced to 12 papers due to accessibility (i.e. not open access) and relevance.

During the systematic refinement process, it was observed that there is also an exponential increase in the number of papers published in the research area selected for systematic reviewing for the more general search string "machine learning "+ "solar energy "+ “rooftop" over the years (cf. Figure 3).

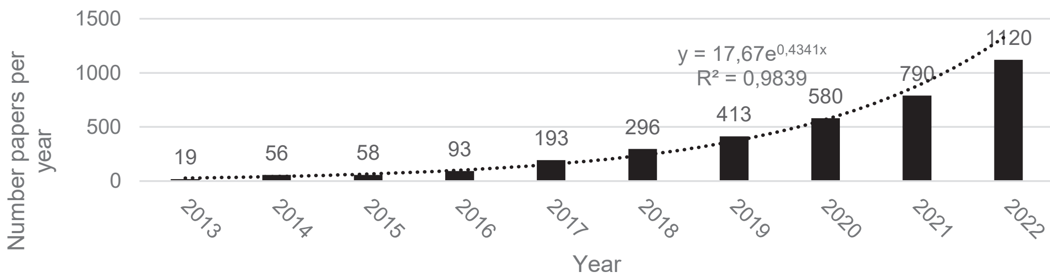

Figure 3: Number of papers published for per year when searching for "machine learning "+ "solar energy "+ “rooftop" showing an exponential increase.

The third case study examined the application of machine learning in district heating and cooling in the context of seasonal thermal energy storages. Be employing the search string "machine learning" + "district heating and cooling" + "seasonal thermal energy storage" and limiting to articles published between 2010 and 2022, we obtained 46 potential articles. Figure 4 displays the number of articles in each year from 2010-2022. The 46 papers were aging reduced to 7 papers based on the following criteria 1. papers that are not open access (21), 2. paper without machine learning application (11), 3. Papers without STES (6), 4. other papers (2), which were not relevant to the study.

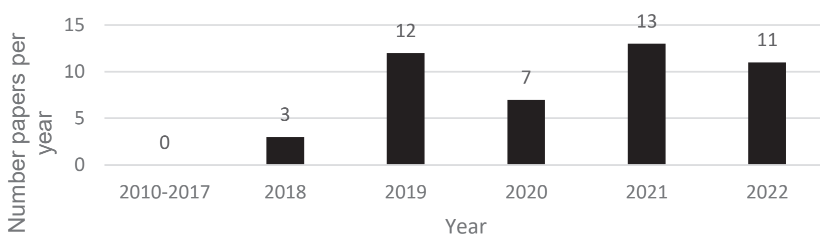

Figure 4: Number of papers published for per year when searching for "machine learning" + "district heating and cooling" + "seasonal thermal energy storage" showing an increase over the years on average.

3. Results

3.1. Machine Learning in Drilling

The application of machine learning or artificial intelligence (AI) has become increasingly prevalent in various industries in recent years [11]. The transition from fossil fuels to renewables to reduce greenhouse gas emissions has led to the rise of renewable energy sectors, such as solar and wind energy, that provide heat and electricity [12,13]. While the share of renewable energy in Europe was 22.2% in 2021 [14], this is still insufficient to meet the renewable energy demands with respect to a climate neutral energy system in the near future [15]. As a result, new technologies are emerging and being developed to support this transition. One sector that requires attention and research to make it a mainstream energy source is geothermal energy, as the energy generation is marginal in both the European Union (3.2%) and Germany (2.5%), despite its potential [16,17,18]. The critical aspect of accessing geothermal energy is developing the reservoir using drilling techniques, which represent nearly 30% to 50% of the costs for a hydrothermal geothermal project and more than half of the total cost on Enhanced Geothermal Systems (EGS) [19]. However, there are also emissions in the drilling process which should be minimized, too [20]. The development of intelligent drilling and completion technologies using machine learning has shown potential to improve the drilling process's efficiency and accuracy [7]. Our study builds upon the comprehensive literature review conducted by Li et al. [7] and strives to offer insights into the particular domains of drilling where machine learning can be applied, as well as the types of algorithms that can be leveraged for specific tasks to enhance efficiency [7]. Li et al. 2022 [7] cite a total of 160 papers, include a number 137 in their analysis over the research fields (cf. Table 1), from which we further analyze 124 while excluding papers where machine learning is not used.

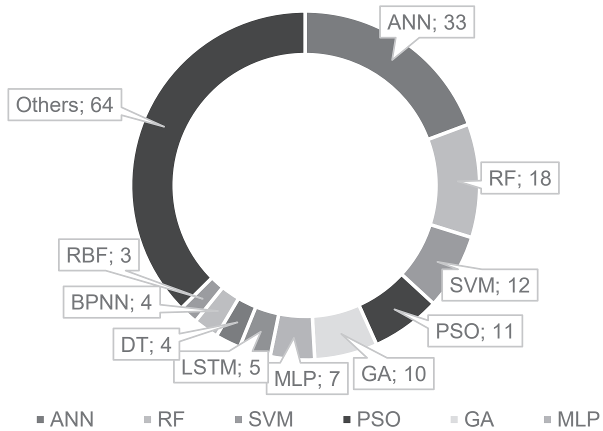

Figure 5: Number of used machine learning algorithms in the 124 papers cited in Li et al. 2022 [7] applying Machine Learning in Drilling

Case Study Results

There are numerous algorithms which have been used in the different papers analyzed by Li et al. 2022 [7] (cf. Figure 5) but among those only five algorithms are highly utilized in most of the fields, which are Artificial Neural Networks (ANN), Random Forests (RF), Support Vector Machine (SVM), Particle swarm optimization (PSO) and Genetic algorithms (GA) (cf. Table 1). These five commonly used algorithms are defined by us based on the repetition and total usage count not less than 10 times across the whole research fields in Li et al. 2022 [7]. Overall, ANNs define the by far most widely used approach and the usage of ANNs is popular in most fields (cf. Figure 6).

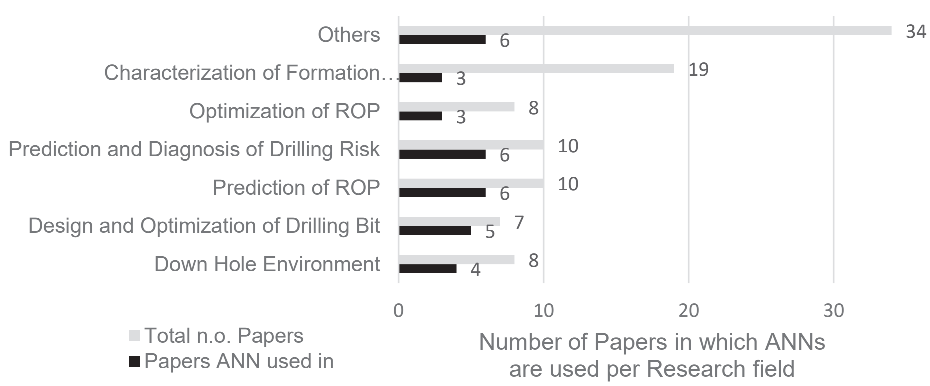

Figure 6: Number of papers per research field in which ANNs were applied in comparison to the total number of papers addressing machine learning in Li et al 2022 [11]

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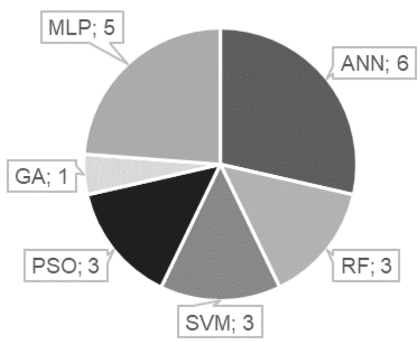
Research Fields	ANN	RF	SVM	PSO	GA
	Algorithms				
Down Hole Environment	4	1	0	0	1
Design and Optimization of Drilling Bit	5	1	0	1	1
Intelligent Prediction of ROP	6	3	3	3	1
Intelligent Optimization of ROP	3	3	0	1	3
Intelligent Design of a well trajectory	0	0	0	1	2
Real time evaluation and optimization of a well trajectory	0	2	0	2	0
Intelligent decision making and control of well trajectory	0	0	0	0	0
Intelligent Characterization of formation properties	3	1	1	0	0
Intelligent Description of wellbore flow behaviour	2	0	1	0	1
Intelligent prediction and diagnosis of drilling risk	6	4	5	1	0
Intelligent control of drilling process	0	0	0	0	0
Intelligent design of hydraulic fracturing	1	1	0	1	1
Intelligent warning and identification of fracturing event	0	1	1	0	0
Productivity prediction and fracturing parameter optimization	1	1	0	0	0
Intelligent completion design and optimization	2	0	1	1	0
Total	33	18	12	11	10

Table 1: Research fields and number of the five most commonly used algorithms in each of these for the analyzed papers from Li et al. [7].

From Table 1, we get an impression of extensively and non-extensively used algorithms in different fields for the five commonly used algorithms. Li et al. [7] analyzed 15 research fields in drilling where machine learning and physical models are used, and from those, whereas 13 fields utilized machine learning for various purposes [7]. Next to the five commonly used algorithms there are few others which are equally often used in some of the research fields, which we want to highlight in the following.



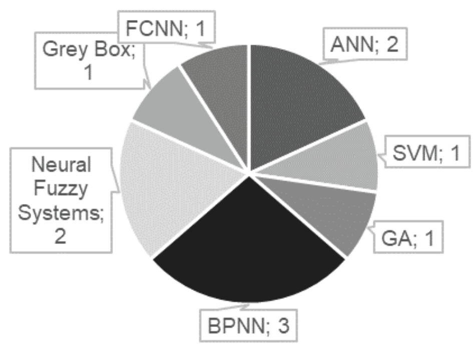


Figure 8: Algorithms used in Prediction of ROP **Figure 7:** Algorithms used in Wellbore Flow Behavior

From Figure 8, we observe that next to the five widely used algorithms, Multi-Layer Perceptrons (MLP) are commonly applied to predict the rate of penetration (ROP). Back Propagation Neural Networks (BPNN) outnumber the five common algorithms in the field of well bore flow behavior (cf. Figure 7). Of course, there are other fields where utilization algorithms next to the five highlighted ones is common - in any case, to achieve the desired results, multiple algorithms should be tested, and there might be no need to choose an algorithm over another. This analysis gives us an impression on how the different research fields of drilling are commonly approached with machine learning techniques.

Depending on the type of process and thus data (dynamic and static) the selection and application of machine learning models is adapted also with respect to performance and robustness. In the two research fields “control of the drilling process” and “well trajectory design”, physical models and control systems were used for stability, control efficiency of the well, and as a strategy to control the trajectory [7]. There are also few fields where machine learning is partially used or not used at all, but instead, physical based models have been used, mostly to control the well trajectory from real time steerable systems (RSS) [7].

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Case study Conclusion and Outlook

The analysis which has been made shows that ANNs are highly used approach in most of the fields, the highest usage of ANNs is in “Intelligent prediction of ROP”, “Intelligent prediction and diagnosis of drilling risk” followed by “Design and optimization of drilling bit” and “Downhole environment perception”. There are few research fields where there is no use of ANNs like “Real time evaluation and optimization of a well trajectory”, “Intelligent design of a well trajectory”, “Intelligent warning and identification of fracturing event” instead other approaches like RF, SVM, PSO were used. As the dominance of ANNs is high one can try implementing them in fields where it has not been used much, yet. Furthermore, RF and SVM approaches were used highly only in “Intelligent prediction and diagnosis of drilling risk” and “Intelligent prediction of ROP”, thus, more studies and implementations could be made in other fields. In the research fields “Intelligent warning and identification of fracturing event” and “Productivity prediction and fracturing parameter optimization” the total use of machine learning is still quite low regarding the total number of papers analyzed by Li et al. 2022 [7], and thus maybe provide good research opportunities for the application of machine learning in drilling.

3.2. Solar Rooftop Potential Quantification

The utilization of solar energy for heat or electricity generation is a highly promising and sustainable alternative to the use of fossil fuels, and the rooftops of buildings represent an underutilized resource for solar power generation [21, 22]. To quantify the potential of rooftop solar energy at a large scale, it is necessary to determine the roof area of buildings that can receive solar radiation, calculate the total solar radiation obtained within the region based on meteorological conditions, and estimate the total solar energy potential with carbon emissions savings and the economic recovery period [23, 25]. However, determining the total roof area can be a challenging task, especially for large regions such as cities or countries [23]. To overcome this challenge, machine learning techniques have been developed to identify and quantify the roof area using aerial and satellite images [24, 26, 28]. This involves collecting initial data from sources such as Google Earth and Copernicus and using semantic segmentation architectures like U-net and Inception-resnet-v2 to identify and segment roofs in the images based on their pixel characteristics [21, 24]. The benefits of utilizing rooftop solar energy are significant, as it enables the local production of renewable power and has enormous potential for reducing greenhouse gas emissions [22, 27]. Studies have shown that rooftop solar energy has the potential to meet a significant portion of a region's energy demands, such as 22% of Europe's energy demand and 15-45% of the energy needs of countries like the United States, Israel, Canada, and Spain [27]. Furthermore, in individual cities like Hong Kong and Seoul, rooftop solar energy has the potential to meet up to 14.2% and 30% of energy demand, respectively [27]. Therefore, there is a clear need to further investigate the potential of rooftop solar energy at a large scale using machine learning and other innovative techniques. This study seeks to provide a systematic literature review of rooftop solar energy measurement based on aerial imaging and machine learning, analyzing various research papers published in this field to compare and address the advantages and disadvantages of different quantification strategies [21, 24, 26, 28]. By doing so, we hope to contribute to the development of more effective methods for quantifying rooftop solar energy potential, which can play a crucial role in the transition from fossil fuels to sustainable energy sources.

Case Study Results

All twelve articles obtained from the systematic literature review process in this study used Google earth as a source for input data. It was also observed that some studies also utilized open-source resources like Copernicus, Open Street Maps (OSM), technical details of PV systems, and aerial pictures accessible using Google Maps' static API. However, the article [24] states that private sources provide high-definition aerial photos for rooftop detection rather than public ones like Google earth.

Semantic segmentation is a major step in the quantification process. It was observed that U-Net is used in most of the studies for semantic segmentation. CNN built on the U-Net is employed, because of its higher performance on small datasets [25]. The paper [26] compared EfficientNet-B3, Inception-resnet-v2, and VGG-19, and Inception-resnet-v2 was chosen due to its superior performance. For semantic segmentation approaches with traditional supervised learning. The article [27] compared three semantic segmentation frameworks: U-Net, PSPNet, and Deeplabv3+ and U-Net was found to be performing better than the others.

In a study conducted by [28] Rooftop Photovoltaic potential has been evaluated using a quick-scan yield prediction technique. It consisted of three primary components. Aerial footage was used to rebuild virtual 3D roof segments for each roof, which were then automatically fitted with PV modules using a fitting algorithm, followed by the calculation of predicted yearly production. After the results were obtained some of the studies had tried to check the accuracy. Twenty randomly chosen roofs were chosen by [29] to compare the model's predictions with estimated real values to assess the findings' accuracy.

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Some common challenges in in the application of machine learning for rooftop solar potential quantification are:

- **Failure to identify pre-existing solar panels:**

  As observed in most of the papers, when the roof area was calculated, much research failed to consider pre-existing solar panels. No differentiation between rooftop space and other surfaces is conceivable within building footprints. This can result in incorrect categorization[30]. When we consider a large area with numerous buildings for the study, they can affect the final output. A machine learning model which can identify and discriminate solar panel area from the rest is crucial to obtain correct results. Apart from solar panels, the machine learning model must be able to distinguish objects like water tanks, Chimneys etc.

- **Limited resolution in the available data:**

  Another Challenge faced by semantic segmentation is the least pixel count. Since the least count is restricted to a pixel, if the major portion of pixel is dominated by a particular object, the Machine Learning model identifies the entire pixel to be that object. Most of the studies though uses public sources like Google earth where semantic segmentation can only be done on available images in given course resolution.

- **Failure to identify inclined roofs:**

  Since only the top view is taken into consideration, the calculated roof area of an inclined roof will be always less than the actual value. This can also have a huge impact on the final output. The machine learning model must be taught to consider this factor, while processing the data, as in some research like the one carried out by [31].

Case Study Conclusion and Outlook

We have systematically reviewed papers in the field of application of machine learning rooftop solar energy quantification and One of the major challenges faced in the quantification process is the identification of preexisting solar panels during semantic segmentation. A solution to this was not identified in any of the papers reviewed and could subject to future research.

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3.3. Machine Learning in District Heating and Cooling in the Context of Seasonal Thermal Energy Storages (STES in DHC)

District heating and cooling (DHC) systems are an important part of the energy sector, providing sustainable solutions to communities. To improve the efficiency of DHC systems, machine learning techniques have been increasingly applied [33]. To supply energy to DHC systems, a source is required, and Seasonal Thermal Energy Storages (STES) can act as an energy source for DHC [34]. STES can help to manage the mismatch between the supply and demand of renewable energy systems, which may occur over seasonal and inter-annual periods. There are four different types of STES: Borehole Thermal Energy Storages (BTES), Aquifer Thermal Energy Storages (ATES), Pit Thermal Energy Storages (PTES), and Tank Thermal Energy Storages (TTES) [35]. Therefore, this study focuses on investigating the application of machine learning in DHC networks with STES, with load/demand prediction, design, and control optimization as the main research categories [33]. This research is motivated by the need to improve the efficiency and reliability of DHC systems while reducing their environmental impact.

Case Study Results

The algorithms used in the seven articles are Artificial neural networks (ANN), genetic algorithms and Non dominant Sorting Genetic Algorithm NGSA-II, which is a multi-objective optimization algorithm which is again the extension of an original NGSA develop by Kalyanmoy Deb in 2022 [4]. Figure 9 gives number of articles used by machine learning methods.

Figure 9: Number of articles with respect to the applied machine learning methods in District Heating and cooling in context of Seasonal Thermal Energy Storages

Various machine learning applications have been applied in different domains, including predictive maintenance, energy demand forecasting, control optimization, and anomaly detection. The papers addressed in this case study had application of machine learning in energy demand forecasting, control optimization, design, and fault detection, specifically in the context of Seasonal Thermal Energy Storages (STES), Aquifer Thermal Energy Storages (ATES), and Borehole Thermal Energy Storages (BTES). However, studies on other types of thermal energy storages, such as Pit Thermal Energy Storages (PTES) and Tank Thermal Energy Storages (TTES), were not present in the papers analyzed and thus not considered in this study. presents the distribution of studies across the various machine learning application categories.

Machine learning applications are applied in differrent ways such as preditcitve maintanence, energy demand forcasting , control optimization, anomaly detection. Here in the study of the selected articles we came accros with the energy demand forecasting, control optimization, design and fault detection. Studies undergo with STES and Aquifer Thermal Energy Storages and Borehole Thermal Enrgy Storages are peformed here, whereas other thermal energy storages such PTES and TTES studies did not show up in the considered papers and are thus neglected. Table 2 shows the three different applied machine learning algorithms in the different categories of application.

Table 2: Applied machine learning algorithms in different categories of application

Category	ANNs	GA	NSGA-II
Energy demand forecasting	1		
Control Optimization		2	1
Design, fault detection	1	1	

Further adressed aspects are:

- In [37], the model predicts the signal of charging and discharging operation and belongs to the category of energy demand forecasting. It was validated to be used in other similar projects; both charging and discharging models have an average accuracy over 95%.
- In [38], optimal based control and model predictive control were applied. MATLAB and a genetic algorithm were used to find an estimate of the global minimum, and a local non-linear minimization routine was used afterwards to refine the calculation.
- In [39], TRNSYS system models and a so-called multi-objective building optimizer (MOBO) are combined to perform the optimization. For this study, the NSGA-II algorithm is used, because it can take care of the constraints, discrete and continuous variables for a multi-objective problem [39].
- In [40], the main objective is to development of a modeling environment able to effectively compare configurational and design choices for multi-energy systems. The core of the Model Predictive Control, that is the optimization function which is Genetic Algorithm, receives information on its settings from the MATLAB organization layer. The role of the Genetic Algorithm is to find the optimal set of instructions for the generation units of the Test Facility for the next prediction horizon. The Genetic Algorithm firstly defines a starting set of instructions following some preset rules. The optimizer then communicates the first set of instructions to the MPC-model.
- In [41], artificial neural networks and geentic algorithms support the fault detection diagnosis. Since the models were trained with laboratory data or data coming from simulations only, they do not achieve a sufficient performance when working with online data. On the other hand, these kind of Fault Detection Diagnosis (FDD) applications show a very promising growth and may be a good option to solve complex FDD problems soon.

In the papers analyzed there are different tools applied for modeling and for data collection. Among these, Transient System Simulation Tool (TRNSYS) seems to be a popular simulation tool within the selected papers which can provide simulated data, if no measured data is available.

Case Study Conclusion and Outlook

The application of machine learning in the energy sector is of utmost importance in the current context. The aim of this study was to provide insights on the use of machine learning in district heating and cooling (DHC) systems, specifically with regards to seasonal thermal energy storages (STES). Despite some research on STES, a comprehensive investigation on this topic remains limited, although Figure 4 depicts an upward trend from 2010 to 2022. The survey highlights the potential field of application of machine learning in various areas such as load demand forecasting, design, fault detection, and control optimization. Artificial Neural Networks

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were found to be the most used method due to their superior performance over other machine learning algorithms. Additionally, the TRNSYS simulation tool was predominantly applied for data simulation. Nevertheless, there is a need for more extensive research in the future to better apply machine learning in DHC with STES, including the development of innovative approaches to improve the collection and analysis of data.

4. Discussion and Outlook

This review paper has addressed applications of machine learning in three different energy systems. In all three case studies, we see a smaller to wider range of machine learning models used for various scenarios in developing the technologies, where ANNs are highly utilized machine learning approaches in both STES in DHC and Drilling. The ANN approach seems to have a high accuracy where prediction is involved as in STES in DHC the energy demand forecast model's average accuracy is over 95%, also in drilling a lot of studies were made using ANNs, e.g. in the prediction of ROP and drilling risk. Genetic Algorithms (GA) on the other hand are mostly used in optimization scenarios in both drilling and STES in DHC. However, in the case of rooftop solar quantification, U-Net and inception resnet - v2 is highly used for semantic segmentation as they have higher performance on small datasets compared with others like PSPNet, Deeplabv3+, and VGG-19.

Some of the possible prospects for development and future research in the considered three case studies would:

1. Machine learning in drilling: application of promising machine learning algorithms in fields, where they were not applied, yet (cf. e.g., Table 1).
2. Machine learning for rooftop solar energy potential quantification: developing techniques to identify pre-existing solar panels and improving various methods to recognize inclined roofs.
3. Machine Learning in district heating and cooling in the context of seasonal thermal energy storages: Due to the limited number of studies, there is a good potential for future research on the of application of machine learning in load demand forecasting, design, fault detection, and control optimization.

5. Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
ATES	Aquifer Thermal Energy Storages
BHA	Bore Hole Assembly
BPNN	Back propagation neural network
BTES	Borehole Thermal Energy Storages
DHC	District heating and Cooling
DT	Decision tree
EGS	Enhanced Geothermal Systems
FCNN	Fully convolutional neural network
FL	Fuzzy logic
GA	Genetic algorithm
LSTM	Long short-term memory neural network
LWD	Logging While Drilling
ML	Machine Learning
MLP	Multi-layer perceptron
MWD	Measured While Drilling
PSO	Particle swarm optimization
PTES	Pit Thermal Energy Storages
RBF	Radial basis function
RF	Random Forest
RSS	Real-Time Steerable System
STES	Seasonal thermal energy storages
SVM	Support Vector Machine
TTES	Tank Thermal Energy Storages

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