JOURNAL OF MECHANICAL ENGINEERING AND SCIENCES
ISSN: 2289-4659 e-ISSN: 2231-8380
VOLUME 20, ISSUE 2, 2026, 11268 - 11275
DOI: https://doi.org/10.15282/jmes.20.2.2026.9.0877

RESEARCH ARTICLE

Experimental evaluation and machine learning-based prediction of a thermal energy storage system's efficiency

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Abstract - Widespread, unabated pollution on account of the rampant use of fossil fuels has caused global warming and climate change. An effective solution to this issue can be either the replacement of fossil fuels with renewable sources or the judicious use of fossil fuels. On this account, the thermal energy storage (TES) system, which can be integrated with conventional power plants to utilise waste heat or with renewable energy systems to store excess energy, could play a major role. The current investigation aims to design and develop a TES system utilising locally available low-cost materials such as silica sand, and then to evaluate its thermal performance using a thermodynamic approach. Besides, the study intends to develop a machine learning model for performance evaluation based on a data-driven approach. Hence, a TES system has been designed and developed, where hot water flowing through a copper tube is the heat source, and 22 kg of silica sand wrapped around this tube acts as the heat storage. Experiments were conducted at a constant hot water flow rate of 0.023 kg/s, and the maximum efficiency of the TES system is noted to be 45.82 %. Further, the experimental data gathered from the testing of the TES system are used to train six different Machine learning algorithms to predict the efficiency. Among the six, KNN, Gradient Boosting, and Random Forest shows very encouraging predictions with R^2 values of 0.92, 0.91 and 0.91, respectively. Therefore, these three algorithms are suitable for predicting the efficiency of a TES system.

Article History
Received : 22 December 2025
Revised : 7 April 2026
Accepted : 2 June 2026
Published : 30 June 2026

Keywords
Thermal energy storage
Energy management
Machine learning
Renewable energy

1. Introduction

Worldwide, pollution is ever increasing due to unabated usage of fossil fuels for energy needs by mankind. As a result, the Earth is experiencing global warming and climate change. Therefore, it is of utmost importance to develop new alternatives for energy needs. Of late, the world is slowly moving towards renewable energy sources and systems. However, developing new alternative sources and systems to exploit is no easy task. So, proper and effective utilisation of available energy is also important. Most of the time, the energy is lost as waste heat in power plants and various processing industries. Extraction of waste heat is challenging. However, technologies such as thermal energy storage (TES) systems can store energy in thermal form [1]. TES systems can be categorised as sensible, latent, and thermochemical [2]– [3]. The working principle of the TES system is very simple; it gets charged by heat energy coming to the system either through a working fluid or a directly heated system from an external source. The TES systems are often integrated with renewable energy systems to mitigate the problems of excess energy storage and fluctuation of energy [2-8]. Li et al. [9] have studied a large-scale 100 MJ cascaded packed bed TES system and observed thermal efficiency as high as 70 to 97%. The thermal efficiency increased on raising the inlet charge temperature. On the other hand Mehraj et al.[10], Abdellatif et al. [11] and Amayreh et al. [12 have focused on TES system design by changing design parameters and materials such as nano particles in phase change materials (PCM). According to Mehraj et al. [10], the study reports appreciable thermal performance between 40 to 70% . Authors such as Mehta et al. [13] and Geng et al. [14] have also studied on PCM based TES systems and observed high charging efficiency as high as 85%. Therefore, a TES system can reach high thermal efficiency as evident from the previous. Nowadays, TES systems are gradually being deployed to conventional thermal power plants to store waste heat [2, 6]. The performance of TES systems is always observed on the basis of their ability to absorb energy and efficiency [8, 9].

Furthermore, prediction of energy absorption and efficiency at different operating conditions is very much crucial for the operation and control of the TES system. These parameters depend on a number of factors such as working fluid flow, inlet and outlet temperature of working fluid, and material properties of storage materials utilized in the TES system. Generally, analytical methods fail to handle these relationships. Moreover, while dealing with large amount of data, the empirical or analytical methods become tedious. Hence, data driven approach such as Machine learning (ML) algorithms can be effectively used in such scenario. Few researchers have utilized such algorithm to predict various performance parameters of TES system. Anagnostopoulos et al. [15] applied Harmony Search ML model to predict thermal performance of a packed bed latent heat TES system. The model is useful for highly non-linear complex environment where it shows an appreciable R^2 value of 0.97, indicating high compliance. Ojih, et al. [16] employed different ML models such as SVR, Artificial Neural Network (ANN), and Decision Tree to identify suitable materials for latent heat-based TES system. Li et al.[17] also employed many ML models such as extreme Gradient Boosting, support vector regression, Random Forest regression, polynomial regression, etc. to predict melting time response of latent thermal energy storage system.

For commerciality of the TES system, the system should not only be efficient but also be low in cost and user friendly. From the open literature, it has been noticed that, among all the TES systems, a sensible-based TES system is

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economically viable and simpler in operation. Again, cheap storage material such as silica sand can further reduce the overall cost. In view of this, the present study aims to fabricate a TES system using locally available, low-cost materials. Furthermore, the in-house-developed sensible TES system requires a comprehensive thermodynamic analysis to understand the heat-transfer behaviour and thermal efficiency. For such analyses, it has been observed that analytical methods are generally tedious and sometimes inadequate, particularly for low-thermal-conductivity materials, where the thermal behaviour is non-linear. Hence, data-driven approaches, such as Machine learning (ML) algorithms, can be used effectively in such scenarios. Predicting TES efficiency using ML algorithms makes it easier to perform system modifications, optimise operating parameters, and, ultimately, minimise thermal losses in advance. Therefore, the experimental results from the in-house developed TES system will be used to train various ML algorithms such as Random Forest, Gradient Boosting, SVR, KNN, Decision Tree and Neural Network and to ascertain the best ML algorithm to predict absorbed energy and efficiency based on R^2 and RMSE parameters. These ML algorithms are specifically chosen as the performance parameters of the TES system are of nonlinear relationships.

2. Materials and Methods

This section discusses the design and fabrication of the TES system, the methods used to evaluate the TES system efficiency and the different ML algorithms employed.

2.1 Design and Fabrication of Thermal Energy Storage System

The present TES system is cylindrical and consists of three distinct sections, as shown in Figure 1. The first section, with the smallest diameter, i.e., 0.09 m, is a hollow copper tube through which the heat-carrying fluid (water) flows at a rate of 0.023 kg/s. A portable hot water geyser is used as the heat source, which supplies the hot water required. The second section is the heat storage section, which is made of 22 kg of silica sand. The silica sand is chosen for the purpose because of its low cost. This section has a diameter of 0.24 m and a height of 0.39 m. Further, a cylinder made with a tin sheet of 0.5mm thickness is used to hold the sand. The third section is the insulating section, which has a diameter of 0.305 m and a height of 0.45 m. The insulating material used here is ceramic fibre. It is important to note here that the insulation is also applied to the circular faces of the first and second sections. Finally, the whole arrangement is embedded in a cylindrical container made of a galvanised iron sheet 1 mm thick. The in-house fabricated TES system is shown in Figure 2. After the fabrication, the TES system is set up at the Mechanical Engineering Department laboratory, Dibrugarh University, Assam, India-786004. The continuous supply of hot water to the TES system is being facilitated by a 1 L geyser. The flow rate of hot water is kept constant at 0.023 kg/s throughout the experiment. This flow rate is monitored by a rotameter. Further, to measure temperature at various critical points, thermocouples are installed. The specifications of various instruments used during the experimental data collection are given in Table 1. Moreover, thermocouples have been calibrated with a laboratory-grade thermometer at five reference temperatures between 20°C and 100°C with a deviation of ±1°C. Further, the rotameter is calibrated using a volumetric collection method and is found to be in good agreement.

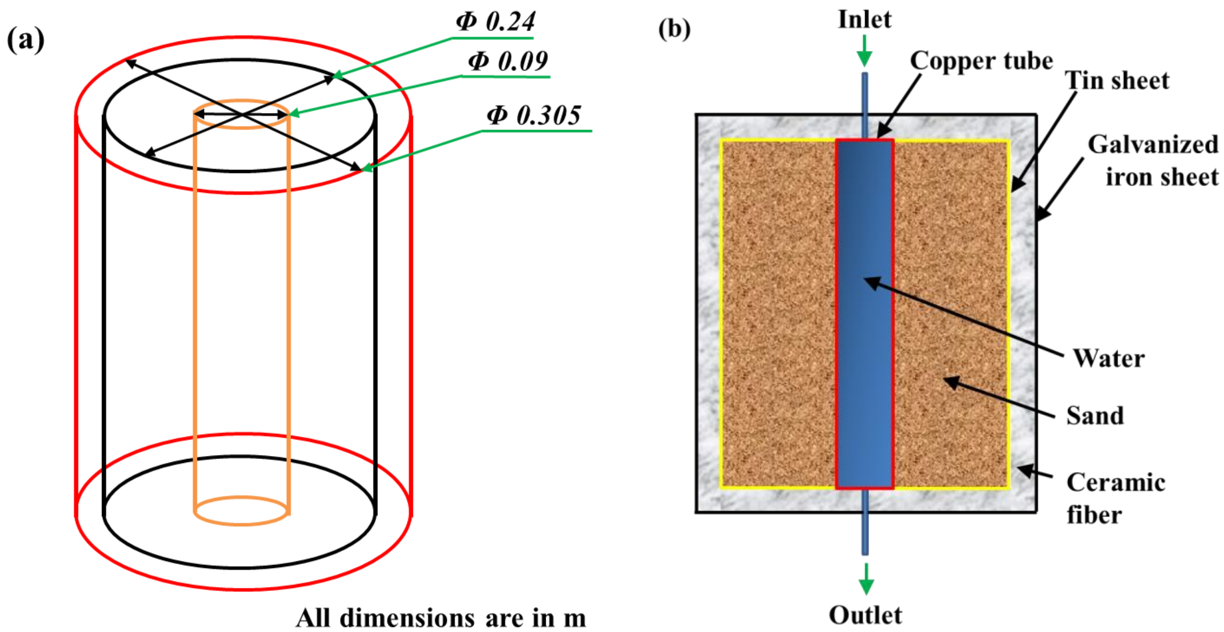

Figure 1. Schematic diagram of the TES system (a) Isometric view (b) Sectional front view

Figure 2. The in-house designed and fabricated TES system

Table1. Specifications of various instruments used

Sl. No.	Name	Make	Specification
1	Geyser	Axhane	Capacity:1 L Copper element of 3000 W
2	Thermocouple	Aptech	Temperature range: 50-110 °C with an accuracy of ±1°C
3	Rotameter	Hilitand	Range: 25-250 L/H or LPH

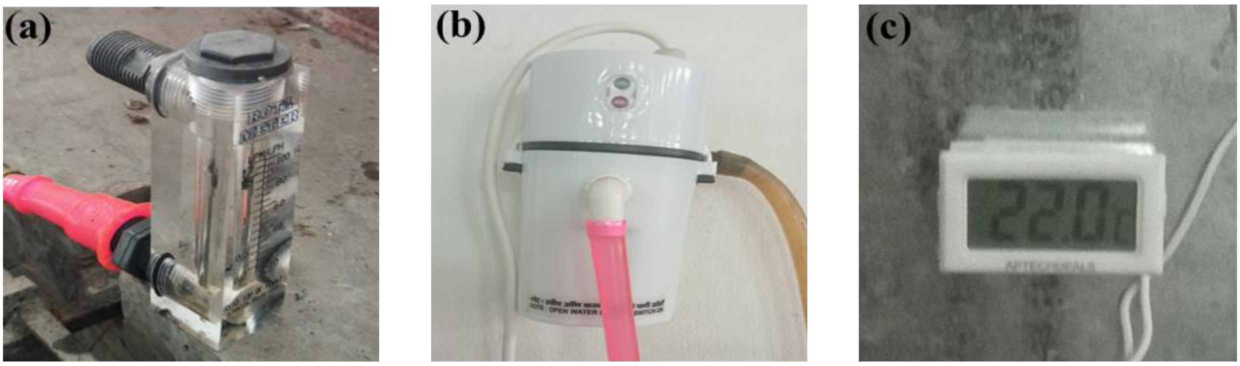

Figure 3. Different measurement tools used in the TES system (a) Rota meter (b) Portable Geyser (c) Thermocouple

2.2 Thermal Energy Storage Efficiency

The TES system efficiency is a key performance parameter, as this parameter indicates how effectively the supplied heat can be absorbed by the system and eventually be used later for various purposes. Furthermore, it is one of the key parameters that determines the commerciality of the system. Therefore, the TES system efficiency is chosen as one of the performance parameters in the present study. To determine the TES system efficiency, we need to find the available energy from heat transfer from hot water to the TES system and the energy absorbed by the TES system.

2.2.1 Heat transfer in the Thermal Energy Storage system

To evaluate the heat transfer rate of the hot water, the temperatures of the water entering and leaving the TES system are measured by the thermocouple placed at the inlet and the outlet. Here, the instantaneous heat transfer rate is calculated by

$$Q_R = \dot{m}C_p(T_i - T_0) \tag{1}$$

where '$\dot{m}$' is the mass flow rate (kg/s), T_i and T_0 are the inlet and outlet water temperature (°C) respectively, and C_p is the specific heat of water (kJ/kgK)

Heat transfer (kJ) in each time interval (600 secs) can be determined by

$$Q_{int} = Q_R \Delta t \tag{2}$$

where, Δt is the time interval.

The heat transfer in the TES system will continue till the steady state is reached. As a result, the total heat transfer to the TES system will increase after each interval, which is termed as the cumulative heat transfer (Q_{cum}). The cumulative heat transfer (Q_{Cum}) of the TES system is calculated by the summation of heat transfer at each interval.

$$Q_{Cum} = \sum_{i=1}^{n} Q_{int} \tag{3}$$

where 'n' is the number of intervals.

2.2.2 Heat absorbed by the TES system

In the current TES system, the hot water is continuously circulating through the copper chamber. The heat transfer takes place by natural convection from hot water to the inner surface of the copper chamber and then via conduction from the copper chamber wall to storage material (silica sand). Copper has high thermal conductivity, so heat transfers easily, while silica sand has low thermal conductivity, which provides thermal resistance and absorbs most of the energy. To minimise heat loss, an insulating chamber (ceramic fibre) has been provided. Furthermore, to record the storage material temperature, three thermocouples have been placed in various radial locations: The first one is placed at the junction of the sand chamber and the heat source (copper tube), the second one is placed at the junction of the sand chamber and the insulation chamber, and the third one is placed in between the two (middle of the sand chamber). To determine the absorbed energy, the average temperature of the storage sand is calculated by finding the arithmetic average of the measured temperatures at each location. For each 10-minute interval (0-10, 10-20, 20-30, etc.), the absorbed heat (Q_{AI}) at an interval is calculated as follows.

$$Q_{AI} = m_s \, C_{ps} \, (T_{sf} - T_{si}) \tag{4}$$

where, 'm_s' is the storage material mass (=22 kg), C_{ps} is the specific heat of sand (=0.83 kJ/kgK). Further, T_{sf} and T_{si} are the final and initial sand temperatures, respectively.

Again, the total absorbed heat (Q_A) can be evaluated by summing the absorbed heat (Q_{AI}) values at different intervals.

$$Q_A = \sum_{i=1}^{n} Q_{AI} \tag{5}$$

2.2.3 Efficiency

The efficiency of the TES system is evaluated by Eq. (6).

$$\eta = \frac{Total\ absorbed\ heat(Q_A)}{cumulative\ heat\ transfer\ (Q_{Cum})} \tag{6}$$

2.3 Machine Learning Algorithms

The aim of the current research is to predict the TES system efficiency by using various machine learning algorithms, such as Random Forest, Gradient Boosting, SVR, KNN Regressor, Decision Tree and Neural Network, on the basis of inlet water temperature, outlet temperature, and the time of operation of the TES system. Therefore, the methodology of assessing the TES system efficiency using ML algorithms will involve five stages,

(a) Data collection from the TES system under different conditions.
(b) Feature selection in the dataset and, if required, normalisation.
(c) Developing the models. Subsequently, training & testing the models.
(d) Cross-validation of models is conducted using 5-Fold Cross-Validation and Hyperparameter Tuning, utilising GridSearchCV and, consequently, performance observation.
(e) Finally, efficiency prediction performance by ML models.
(f) For the current TES system, inlet water temperature, outlet water temperature, and the time of operation of the TES system have been considered as the independent variables or features for model training. The target output is the efficiency of the TES system. Then, ML models such as Random Forest, Gradient Boosting, Support Vector Regressor, K-Nearest Neighbours (KNN), and Neural Network have been considered in the present investigation. The dataset was divided into 70% training and 30% testing subsets for the models using a random stratified approach. The numerical features are scaled using the *StandardScaler* method from *Scikit-learn*.

Furthermore, to counter overfitting and further generalise the models, a 5-Fold Cross-Validation approach is used. This approach groups the training datasets into 5 subsets. In every iteration, four subsets are used for training, and one is used for testing. The process takes place five times. The average performance of the model is considered. Furthermore, Hyperparameter Tuning is conducted utilising *GridSearchCV*. For that matter, each ML algorithm is embedded in a Pipeline for data integrity. Finally, the model performance was assessed in terms of R^2 and root mean square error (RMSE) values. The Random Forest algorithm makes multiple decision trees for results, and these results are averaged to reach a prediction [17]. This process is very useful for prediction. Similarly, Gradient Boosting also employs decision trees for results in a series manner. In this process, a decision tree is initially built to predict the result, then checked for errors, and this iterative process repeats until the residual errors are minimised. The algorithm is very useful for capturing nonlinear relationships in data [18]. On the other hand, Support Vector Regressor (SVR) creates a straight line to fit the data normally. If the data is very complex, a simple straight-line fit does not work. In such a case, the SVR adds new dimensions to the data, thereby separating data points clearly. The new data points can be fitted easily in higher-dimensional spaces with a tolerance limit. In the case of the KNN Regressor, it works by identifying the k nearest data points to the predicted value and then averaging their values to make the prediction. It is a simple technique, but not useful for large data [19]. Lastly, the Neural Network (MLP Regressor) consists of a network of neurons [20]. Neurons learn patterns in input data to predict an output based on this learning. Typically, a neuron takes the input data, also known as a feature. Each input is assigned a weight that distinguishes it from the others based on importance. The neuron adds all the weighted inputs along with a bias. The bias is a small number that helps in shifting the results. Then this sum is further processed through sigmoid or ReLU functions for output. The importance of this function is that it introduces nonlinearity to the computation process. Then the output goes to the next neuron, acting as input data for improved prediction.

3. Results and Discussion

The results and discussion sections are divided into two sections: experimental evaluation of the TES system's efficiency and the application of machine learning algorithms to predict the TES system's efficiency based on inlet water temperature, outlet water temperature, and the TES system's operating time.

3.1 Experimental Evaluation of Efficiency

In the current investigation, the TES system was put to the test at the laboratory of the Mechanical Engineering Department, Dibrugarh University, Assam, India. The test was conducted in September 2025, and the ambient temperature recorded on that day was 31°C. The hot water was supplied at a constant flow rate of 0.023 kg/s. The test was conducted for a period of 3 and a half hours (210 minutes). The temperature at the inlet and outlet of the system was recorded. Besides, the temperature near the copper chamber, the temperature of sand near the insulation and the temperature at the outer surface of the outer enclosure were recorded. The heat transfer rate and heat absorbed by the TES system were determined. Finally, the efficiency of the TES system was determined at each interval. Important parameters such as temperature at inlet (T_i), temperature at outlet (T_o), average sand temperature (T_S), Time duration (Δt), heat transferred in an interval (Q_{int}), cumulative available energy (Q_{Cum}), total heat absorbed (Q_A) and Efficiency (η) at different times are listed in Table 2. Due to a smaller differential temperature at the start, a large percentage error occurs for the data set corresponding to a 10-minute time. Therefore, excluding this data set, the evaluated cumulative energy available from heat transfer from water, the absorbed energy by the TES system, and the efficiency of the TES system are plotted against time in Figure 4. It has been observed that the efficiency reaches a maximum value (45.82%) within 40 minutes of operation, and it gradually decreases. It is due to the reason that the storage material is approaching saturation towards the latter part of the operation. Besides, heat losses to the surroundings and low heat transfer.

Table 2. Experimental observation of the TES system

Time (Min)	T_i (°C)	T_o (°C)	T_S (°C)	Δt (Sec)	Q_{int} (kJ)	Q_{Cum} (kJ)	Q_A (kJ)	η (%)
0	29.5	30.4	31.58	0	0	0	0	0
10	58.2	57.8	31.80	600	23.0957	23.0957	4.0172	17.39
20	60.2	57.6	34.54	600	150.1219	173.2176	54.0496	31.20
30	59.7	58.6	37.20	600	63.5131	236.7307	102.6212	43.35
40	59.0	58.6	38.10	600	23.0957	259.8264	119.0552	45.82
50	58.6	57.8	38.90	600	46.1914	306.0178	133.6632	43.68
60	58.9	57.3	39.00	600	92.3827	398.4005	135.4892	34.01
70	58.5	57.5	40.00	600	57.7392	456.1397	153.7492	33.71
80	70.3	57.3	54.30	600	750.6096	1206.7493	414.8672	34.38
90	71.6	64.6	57.40	600	404.1744	1610.9237	471.4732	29.27
100	72.1	66.1	60.90	600	346.4352	1957.3589	535.3832	27.35
110	72.5	69.8	62.00	600	155.8958	2113.2547	555.4692	26.29
120	72.5	67.0	63.50	600	317.5656	2430.8203	582.8592	23.98
130	73.3	66.5	64.90	600	392.6266	2823.4469	608.4232	21.55
140	72.8	67.5	66.10	600	306.0178	3129.4646	630.3352	20.14
150	72.6	67.1	66.70	600	317.5656	3447.0302	641.2912	18.60
160	72.6	67.1	67.00	600	317.5656	3764.5958	646.7692	17.18
170	74.5	66.9	67.50	600	438.8179	4203.4138	655.8992	15.60
180	74.3	68.1	68.80	600	357.9830	4561.3968	679.6372	14.90
190	74.1	68.3	69.10	600	334.8874	4896.2842	685.1152	13.99
200	74.4	68.0	69.50	600	369.5309	5265.8150	692.4192	13.15
210	74.5	68.3	69.80	600	357.9830	5623.7981	697.8972	12.41

The sand further contributes to the low efficiency of the TES system, a common issue in such sand-based systems. For a sensible heat-based TES system as ours, Mehraj et al. (2025) also reported efficiency in the same range as ours [10]. In another study by Li et al. (2025), efficiency ranged from 70% to 97% upon increasing the temperature to 180°C [9]. As the TES system in the present investigation is designed for integration with solar-based systems such as solar trough collectors or flat plate collectors, such a high temperature is not possible to reach, and hence, the evaluated TES efficiency within our tested temperature range of 20°C to 75°C conforms to the previous studies reported by various authors [10].

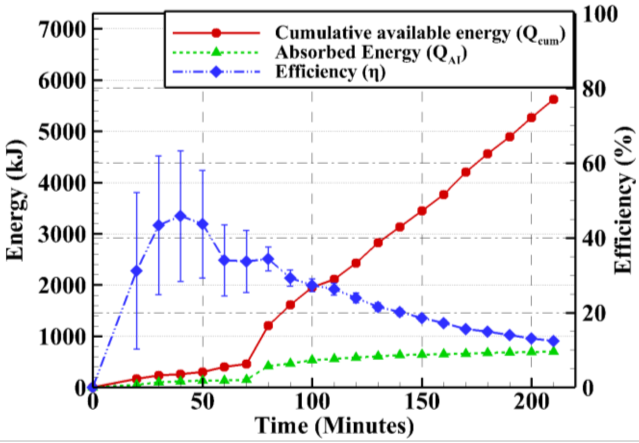

Figure 4. Variation of cumulative available energy absorbed, energy and efficiency with time

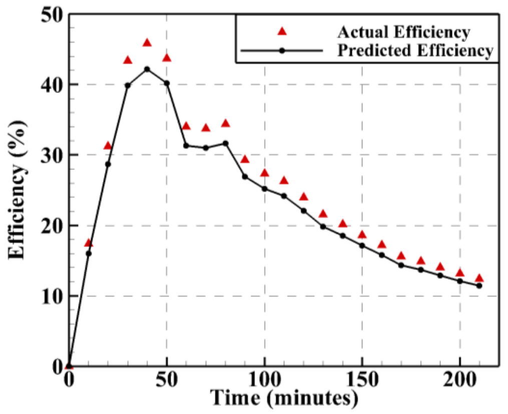

Figure 5. Comparison of actual efficiency with predicted efficiency by Gradient Boosting model

3.2. Application of Machine Learning Algorithms

The data set obtained from the experimental investigations (excluding data corresponding to 10-minute time intervals) is utilised by six different machine learning algorithms to predict the TES system efficiency based on inlet water temperature, outlet temperature, and the time of operation. The ML algorithms considered herein are Random Forest, Gradient Boosting, SVR, KNN Regression, Decision Tree and Neural Network. All six models have been trained and validated using a 5-fold cross-validation approach. Then, GridSearchCV is used to optimise all the hyperparameters. Finally, model performances have been observed, and R^2 and RMSE values are listed in Table 3. Among the six ML models, KNN has performed the best with the highest R^2 and lowest RMSE values of 0.92 & 3.01, respectively. This is followed by the Gradient Boosting and Random Forest models, each with an R^2 value of 0.91. Further, the ML methods with decreasing values of R^2 are SVR (0.86), Neural Network (0.65) and Decision Tree (0.57) models. It is observed that the KNN model, along with Gradient Boosting and Random Forest, achieves very good R^2 values, indicating a strong relationship between the dependent and independent variables. The KNN algorithm looks for nearby data points and does not need any fixed equation to start. Rather, it learns the pattern from the data itself. Therefore, in the case of the TES system, where temperature changes over time and affect the efficiency, it can identify the pattern and give a good prediction. Gradient Boosting and Random Forest, as ensemble learning models, can keep adding small models, with each new model correcting the mistakes of the previous ones. The resultant prediction combines all the outputs to get the final output. Thus, these two models could capture the non-linearity in the thermal behaviour of the TES system. SVR is sensitive to kernel & hyper parameters for tuning the model. With limited data, the model might have difficulty in capturing non-linearity in thermal behaviour that took place in the TES system. Further, Neural Network and Decision Tree models require a large dataset to learn patterns. Otherwise, it could result in underfitting or prediction errors, as is evident in the present case. Therefore, these three models can efficiently predict the dependent variable, i.e., the efficiency of the TES system. Hence, these ML models are the potential predictive algorithms for future studies in the field of obtaining efficiency of a sensible heat-based TES system. Again, the actual efficiencies are compared with the predicted efficiencies by the Gradient Boosting model at different times in Figure 5. A very encouraging match between the two data sets is observed from Figure 5.

Table 3. R^2 and RMSE values of algorithms

Sl. No	ML models	R^2	RMSE
1	KNN	0.92	3.01
2	Gradient Boosting	0.91	3.25
3	Random Forest	0.91	3.32
4	SVR	0.86	4.02
5	Neural Network	0.65	6.43
6	Decision Tree	0.57	7.15

4. Conclusions

A sensible heat-based TES system is successfully designed and fabricated in-house. The heat storage material used in the system is locally available, low-cost silica sand. Further, the TES system is tested, and the efficiencies at different times are measured. The TES system achieves the highest efficiency of 45.82% in the first 40 minutes of charging, which is its optimal efficiency. It shows that the system gets charged mostly in the first 40 minutes of operation. Again, the experimental data obtained are used by six different ML algorithms to predict efficiency, with the aim of finding the best-suited algorithms for this non-linear relationship. For the ML algorithms, efficiency is the dependent variable, whereas inlet water temperature, outlet water temperature, and the TES system's operating time are the independent variables. It is found that the KNN model shows the best results with very good R^2 and RMSE values of 0.92 & 3.01, respectively. Further, Gradient Boosting and Random Forest models also show very encouraging results with R^2 values of 0.91. Therefore, it can be inferred that the KNN, Gradient Boosting and Random Forest algorithms are among the best suited for efficiency prediction of the current TES system. It is important to note that the experimental data employed in the ML algorithm analysis are for a fixed rate of flow. Future work may focus on incorporating datasets from multiple flow rates to improve model generalizability and applicability to dynamic operating scenarios.

Acknowledgments

The authors are indebted to the Department of Mechanical Engineering, DUIET, Dibrugarh University, Assam, for their help and support.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interests

The authors declare no conflicts of interest.

CRediT Authorship Contribution Statement

Madhurjya Saikia: Investigation; Data curation; Writing - orginal draft
Saroj Yadav, Dipankar Das: Conceptualisation; Verification; Investigation; Writing- review & editing; Supervision
Partha Protim Borthakur: Analysis; Writing- review & editing
Rupam Deka: Investigation; Writing-review & editing
Pranjal Sarmah: Methodology; Data curation; Writing- review & editing

Availability of Data and Materials

The data supporting this study's findings are available on request from the corresponding author.

Ethics Declarations

This study did not involve human participants or animals. Ethical approval was therefore not required.

Generative Artificial Intelligence Declarations

The authors claim that artificially intelligent-assisted technologies, such as generative AI, were not used to generate content, ideas, or theories. We have just utilised AI to enhance readability and refine the language. This was used with extreme human control and oversight. The authors take full responsibility for reviewing and approving the content.

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