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Research Article

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Using Machine Learning Algorithms to Detect Anomalies in the Solar Heating System

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Abstract

This article explores the use of machine learning algorithms to identify anomalies in the solar heating system. A solar heating system that has been developed consists of several parts to simplify the description and modeling process. The authors propose a new architecture for neural networks based on ordinary differential equations. The idea is to apply the new architecture for practical problems of accident prediction (the problem of extrapolation of time series) and classification (classification of accidents based on historical data). The developed machine learning algorithms, artificial intelligence techniques, the theory of differential equations-these directions allows us to build a model for predicting the system's accident rate. The theory of database management (non-relational databases)-these systems allow you to establish the optimal storage of large time series.

Keywords: Flat solar collector; Solar heating system; Machine learning; Algorithm

Introduction

IRENA [1] examined how to improve the performance and reliability of renewable energy systems to reduce the associated investment and operating costs. The work by Niu [2] investigated several Machine Learning (ML) applications in the Prognosis and Health Management (PHM) program aimed at improving the availability and performance of complex systems. The article uses Deep Learning (DL) methods to develop a system in lithium-ion batteries Lui et al. [3] and others.

Solar Hot Water (SHW) systems are commercially mature applications of solar thermal technology for residential and low temperature industrial applications. Paper by de Keizer et al. [4] developed performance predictions for planar solar collectors to assess system health and assist in performing maintenance planning tasks.

The article by Ghritlahre et al. [5] used various versions of artificial neural networks. Performance forecasting and efficiency analysis under various meteorological conditions are studied in SHW systems, solar heat pump and heat storage systems with various neural network models such as Multilayer Perceptron (MLP), Radial Basis Functions (RBF) and Adaptive Fuzzy Network Based System Output (ANFIS). In this work Kalogirou et al. [6], a fault diagnosis system was developed, in which the monitored data are compared with the predicted values, which makes it possible to detect faults in solar collectors with good results. In article by Lipton et al. [7] with the help of memory (LSTM-RNN), implemented for the analysis of long-term time dependences. In this work by Srivastava et al. [8], the study of LSTM neural networks for predicting global horizontal illumination for the day ahead was compared with satellite data. The article by Leva et al. [9] developed controls with electrical grids for sizing a renewable energy storage system.

In this paper Correa-Jullian et al. [10], the ANN, RNN and LSTM architectures were developed to predict the temperature in the SHW system; and compared under similar conditions to highlight their strengths and weaknesses. By comparing the prediction errors of a model generated using nominal data and data caused by errors, an error-based threshold is determined for classifying the health status of the system. The article Kalogirou et al. [11] investigated synthetic data that is generated in TRNSYS under nominal conditions and conditions caused by anomalies. TRNSYS simulations used manufacturer's ratings, including design temperatures, equipment sizes and capacities, and control scheme for each subsystem. Paper by Souliotis et al. [12] presents a study that combines a suitable Artificial Neural Network (ANN) and TRNSYS to predict the performance of an Integrated Collector Storage (ICS) prototype.

The article by Amirgaliyev et al. [13] considers the experimental tests on the tubular solar collector with absorbing shield. Aim of the experiment thereof is research of thermal characteristics of tubular solar collector for producing hot water. During the experiment there have been specified the thermal performance, solar installation circulation, water heating dynamics, which maintain water heating at the expense of solar and electric power combined use. This paper by Yedilkhan et al. [14] considers the main parameters of the solar collector with thermosyphon circulation for the solar heat supply system. There was developed a flat solar collector construction with thermosyphon circulation wherein the heat transfer coefficient is increased by removing the additional partitions between a panel and heat insulation. The solar collector's efficiency reached by the availability of a tank and thermal pump in the construction where a condenser and evaporator executed the form of a heat exchanger of «spiral in spiral» type and heat exchanger pipe connections are one above another, which allows increasing the square and heat exchange intensity. The outcome of the study is a description of the mathematical analysis of the heat transmission process in the tank accumulator. In the work by Amirgaliyev et al. [15] here in we have carried out numerical solutions of statistical data and construction of the prediction model by means of machine learning program LightGBM for the solar heat supply system. Gradient Boosting Decision Tree (GBDT) is a popular algorithm of computer-aided learning and it has quite a few effective implementations, such as XGBoost and pGBRT. For solving the problem solution definite algorithm there have been conventionally selected the thresholds, in order the right-side purpose oriented variable drops down, entry variables grow. We have developed four algorithms, which show, how there is established the possibility of constructing the functional dependences between inlet and outlet parameters by means of machine learning program Light GBM. From conducted numerical experiments we can draw a conclusion, that the

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Light GBM is considerably well trained, it accelerates training process and further, we can say, the LightGBM package has been well enough trained for the solar heat supply systems. The article by Amirgaliyev et al. [16] considers the solar-driven resources of the Republic of Kazakhstan. To assess the solar energy potential, falling onto the territory in any region, it is necessary to have data on the solar energy potential. Based on actual observations and theoretical calculations generalizing, there exists the data: annual and latitudinal motion of possible monthly and annual sums of the direct solar irradiation falling onto the perpendicular surface under the conditions of clear sky, data on sunshine duration, daily motion of solar radiation for typical days of the year, maps of distributing the average monthly radiation sums for June and December on the territory as well as the maps of distributing «technically applicable and economically profitable solar capacity», developed criteria of defining the notion thereof. All solar systems estimates upon assessing the solar-driven resources on Kazakhstan territory are based on quantitative characteristics of the direct solar radiation onto the horizontal surface from which there might be done recalculation from the horizontal to inclined plane of any orientation. Proceeding from the results of average values of the direct, total irradiation and duration of the sunshine statistical treatment there have been differentiated five zones and compiled a histogram characterizing the possibility of introducing the solar plants onto Kazakhstan territory.

Prediction of accidents and stable operation of technical devices is an urgent task in various fields. The forecast must be done in advance in order to ensure the high-quality operation of the devices. It is logical that this problem is cost-effective compared to the problem of complete replacement or overhaul of a specific technical device. Determination of accidents can be based on an understanding of how the main components of the device work. If all the components are working properly, the performance is better, and therefore there is less chance of an accident. Modern research has shown that continuous monitoring and analysis of components remains the most important task for many companies.

Currently, the only practical way to monitor the health of such components is to detect complex signals such as vibration, pressure and electrical current generated by technical devices and collected by industrial sensors. It is often difficult to extract useful information from such indirect, mixed and noisy signals, so there is a need for data analysis to extract specific characteristics from these complex signals. A machine learning algorithm is proposed for the regression and time series problem. When the model identified the deviation between the trained regression model and the actual value, the abnormal behavior of the technical device was correlated. Light GBM is used to build a regression model, the model results for the RSME metric are about 1%.

Research Methodology

Developed master control of solar thermal system is able to measure characteristics of thermal solar installation with chemical coating, which might be compared to similar features of traditional double circuit solar installation with thermosiphon circulation.

Flat solar collectors with thermosiphon circulation are used for transformation of falling solar irradiation into thermal power. That energy is accumulated in the form of sensible heat in the reservoir, designed for fluid storage and it is used, as necessary, for heating premises and water. Figure 1 shows the double circuit solar installation with thermosiphon circulation, offered in the works.

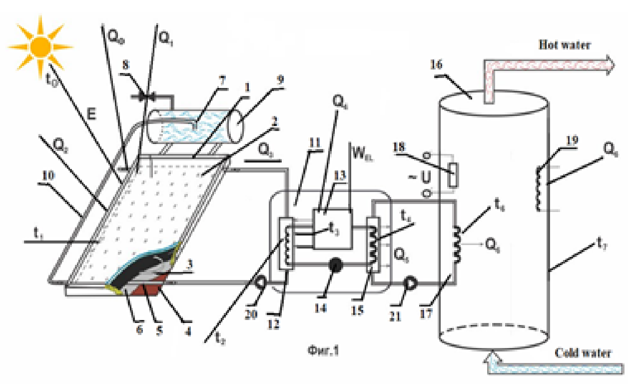

Figure 1: Principal diagram of double circuit solar installation with thermosiphon circulation.

Operation of the installation, being offered is fulfilled as follows. Solar power E with temperature t0 is absorbed by the solar collector 1, with temperature t1, and heating the solar energy flow goes through translucent insulation double glass 2. The heat, received from solar flow, heats the liquid in coils 3, which is removed from the collector, and its place is occupied with cold water from water pipe by means of the cold water valve 8, and from the dozer tank syphon 7 there takes place constant thermosiphon circulation with the help of circulation pipe 10. Further, the liquid goes to a thermal pump 11, which consists of condenser's evaporator 12 with temperature t2, in which the heat exchanger, made in the spiral form absorbs transfer medium heat, decreases its temperature lower than that of the atmospheric temperature (Q2) by means of speed control valve 14, thereby promoting the additional heat absorption from atmospheric air. The diagram, as well, shows solar irradiation, reflected from semitransparent coating (Q0) and surface of absorbing panel (Q1). In the thermal pump there is fulfilled the transfer of heat carrier power, with relatively low temperature to condenser heat exchanger transfer medium 15 in the spiral form with higher temperature t2, which increases the square, as well the heat exchange intensity. To execute such cycle there is used a compressor 13 with temperature t3, with an electric drive 17. Further, by means of condenser heat exchanger 15 with temperature t4, the heat from the thermal pump (Q5) is transferred to the heat exchanger accumulator tank Q6 with temperature t6 of heating system 18. As the installation has two circuits, it is equipped with automatic circulation pumps19 and 20 for liquid circulation between solar collector and evaporator, condenser and tank-accumulator. Water temperature reaches the required technological level and water is transferred to a consumer for hot water supply and buildings heating.

Solar heat supply system with solar collector, covered with chemical etching has been constructed at the Institute of Information and Computer technologies in Almaty city, republic of Kazakhstan (latitude 45° 24'5 "n. l., longitude 9°14'58"E). The installation has been developed without cable grooming; it is cheaper, than accessible solution and simpler in implementation to avoid the problems of communication with installation inside the building, far from a solar panel. The system anticipates installing of external heat exchanger, designed for modeling hot water consumption or dissipating the heat at temperature inside the tank exceeding the fixed value, set as a maximum threshold. Control system consists of external wireless solar power source unit with autonomous energy supply, which transfers the data on solar panel temperature (T1) to the inner control unit, which receives data and manages the system, controlling temperature values and states of two electric pumps.

The methodological basis of the research will be:

Machine learning algorithms, artificial intelligence techniques, the theory of differential equations - these directions allow you to build a model for predicting system accidents.

The theory of database management (non-relational databases) - these systems allow you to establish the optimal storage of large time series.

ANN modeling is done in two stages; the first step is to train the network and the second is to test the network with data that is not used for training. Although the training is time consuming, they are very quick to resolve any operation. ANN is trained with a suitable training method to perform a specific function by adjusting the weight values. The process continues until the network output matches the output. Changing weights and biases reduces the error between the mains output and the desired output. The training process ends when the error falls below a certain value. The network uses a learning mode in which inputs are presented to the network along with the desired result and the weights are adjusted so that the network tries to produce the desired output.

The network architecture selected using input and output parameters are shown in Figure 2. The input parameters for this present work are

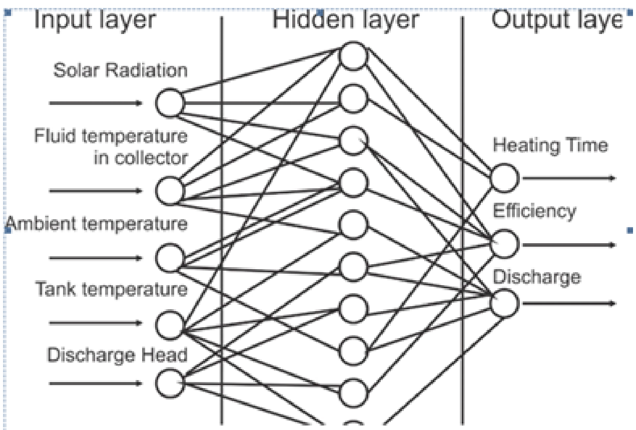

Figure 2: Network architecture for a flat panel solar collector with a heat pump.

solar radiation received per unit area, heat pump blower and ambient temperature. Solar radiation is the energy of solar irradiation that falls on a flat solar collector to heat water appropriately over time in a specific cycle of operation. The second input is the heat pump blower and the real work is done for a delivery depth of 0.5 m. The third input parameter, the ambient temperature is also recorded for each heating time value. The output parameters in this work are the heating time for each cycle of operation, the efficiency of the heat pump and the flow from the system.

Mathematically, the efficiency of the system can be written in the following form

$$\eta = \frac{\rho_w * V_w * g * H}{I_\beta}$$

Where the head in m, is the volume of raised water and is the intensity of solar radiation in W/m2.

The obtained experimental data is used to train the network.

Here, 100 datasets are used to train the network. Input data is divided into training sets (70%), test kits (15%) and testing sets (15%). This simulation used a single hidden layer learning algorithm. By lowering the propagation of error from the output layers to the bottom layer, the algorithm optimizes the synaptic weight (hidden layer and input layer). The ANN model approximates the desired result from each iteration so that errors are reduced and the errors are then passed to the ANN to adjust the weights. The network is trained to achieve the selected error target. In this work, the sigmoid transfer function Tan is used as the activation function for the buried layer and the output layer Table 1.

Table 1: Correlation coefficient for different numbers of neurons.

The number of neurons in the hidden layer	Correlation coefficient
7	0,99988
9	0,99978
12	0,99965
14	0,99897
16	0,9984

$$RMSE = \sqrt{\frac{(X_i - Y_i)^2}{N}}$$

$$CC = \frac{N\sum(X_i * Y_i) - \sum X_i \sum Y_i}{\sqrt{(N\sum X_i^2 - (\sum X_i^2)(N\sum Y_i^2 - (\sum Y_i^2))}} \backslash$$

$$APE = \frac{1}{N}\sum\left(\frac{abc(X_i - Y_i}{X_i}\right) * 100$$

Where are Xi –Experimental values and Yi –ANN predicted output values.

Results and Discussion

In this study, experiments with a heat pump were carried out for a depth of 0.5 m. Experimental work was carried out continuously for one week. The flat plate solar collector was exposed to radiation every day from 7:00 am and the heat pump was ready to perform its first cycle by 11:00 am.

Figure 80 shows the time variation of solar radiation on a sunny day. The maximum solubility of solar radiation per day with experimental data was between 11:00 and 17:00 as shown in Figure 3.

The heat pump gives the best performance during this time interval and the experimental results are exactly the same. The heating time at noon is much shorter compared to other times.

Figure 3 shows the change in ambient temperature over time. The graph shows the data of the solar radiation curve, which is the solar radiation, which directly affects the ambient temperature.

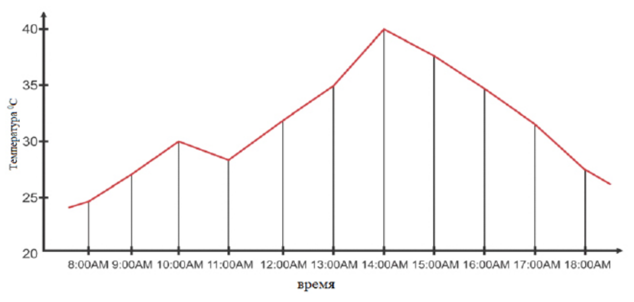

Figure 3: Change in solar radiation over time on a sunny day.

Figure 4 shows the exact change in pressure over time when the heat pump is at a depth of 0.5 m and fluctuates between the two limits.

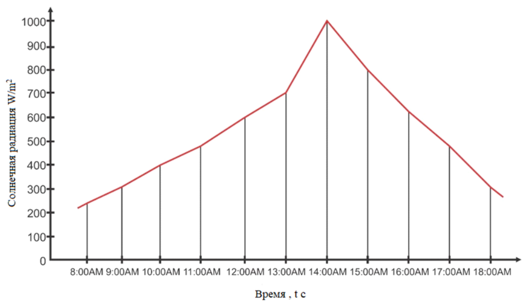

Figure 4: Change in ambient temperature over time.

Table 2 shows the number of cycles per day, flow rate and operating efficiency performed for the heat pump. The efficiency depends on the number of cycles per day and the performance of the heat pump.

Table 2: Number of cycles per day,consumption and efficiency.

No	Pressure (m)	Number of cycles per day	Unloading (liter/day)	Efficiency
1	0,5	6	30	0.16

To find the equivalent heat transfer coefficient of conductivity and convection from the absorber plate to the working fluid for numerical predictions, the commercial CFD (Computational Fluid Dynamics) software package ANSYS FLUENT 19.0 was used to determine physical models and solve the conjugate heat transfer between the liquid and the solid of the absorber, copper tubes and working fluid (water).

The angle of inclination of the flat solar collector was chosen equal to β=45°, since the city of Alma-Ata is located in the center of the Eurasian continent, in the south-east of the Republic of Kazakhstan, at 43° north latitude, therefore the optimal location of the angle of inclination of the collector will be about 45°, but if we use collectors all year round, then the angle of inclination of the collector to the horizon is recommended to choose 15 degrees less latitude. In our case, it's about 45 degrees. It can also be said that if the actual orientation of the solar collector on the object differs less than 15 degrees on the horizon from the zero orientation to the astronomical south, then the losses are not so great, but if it is technically impossible to implement these requirements, then the efficiency of solar systems falls and investments in them will never pay off.

The angular effective zone of operation of flat and vacuum tubular collectors is about 45 degrees in each direction from the perpendicular to the surface, that is, in total about 90 degrees, and the total solar radiation on the inclined surface was set as Gg=750 W/m2. The outside wind speed was set to w=2.5 m/s, and the ambient temperature was 20°C. The thermal efficiency of the collector (ng), based on the total collector area (Ag), was then calculated based on the model of the concentrated reservoir capacity by specifying the collector input temperatures.

For further development and research, TRNSYS simulations were investigated, which were used to evaluate performance, including design temperatures, dimensions and capacities of a dual-circuit solar system, as well as a control scheme for each subsystem.

Four temperature conditions at the inlet, 10°C, 30°C, 50°C, 70°C, were considered to obtain equivalent heat transfer coefficients of absorbing plates to predict the thermal characteristics of the collector as shown in Figure 5.

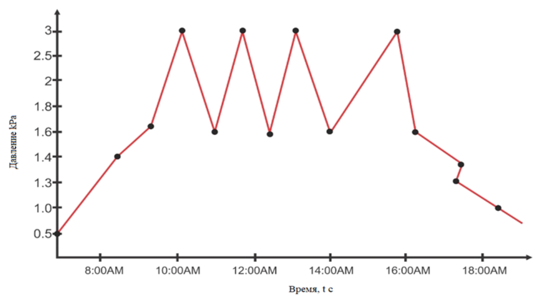

Figure 5: The exact change in pressure over time.

To test the reliability of the new type TRNSYS TYPE 15-3 compared to the standard TYPE 45a, the simulation results are compared with the corresponding experimental data. In particular, the temperature of the working fluid at the inlet/outlet from/to the collector, the mass flow rate of the thermosiphon and the resulting useful thermal power were investigated as.

As can be seen from Figure 6, the temperature near the serpentine tube is much lower between adjacent parallel parts of the tube. The temperature gradient is due to the efficiency of the absorber plate.

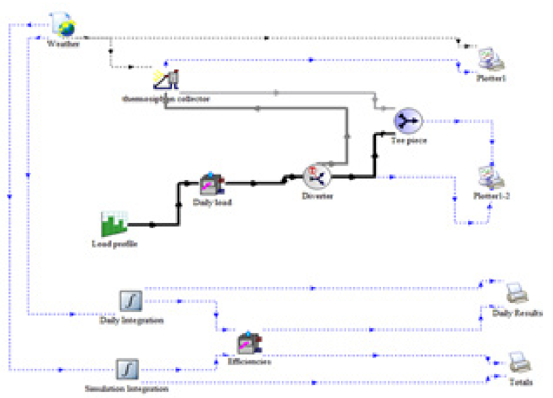

Figure 6: TRNSYS diagram of the simulated thermosiphon system of the solar collector.

As can be seen in Figure 7, the temperature contour of the collector plate-absorber with an inlet temperature of 30°C. is shown. In contrast to the coil-type temperature circuit with a tube, it was found that the maximum temperature of the collector plate-absorber under the same temperature conditions at the inlet is significantly lower than that of the first one.

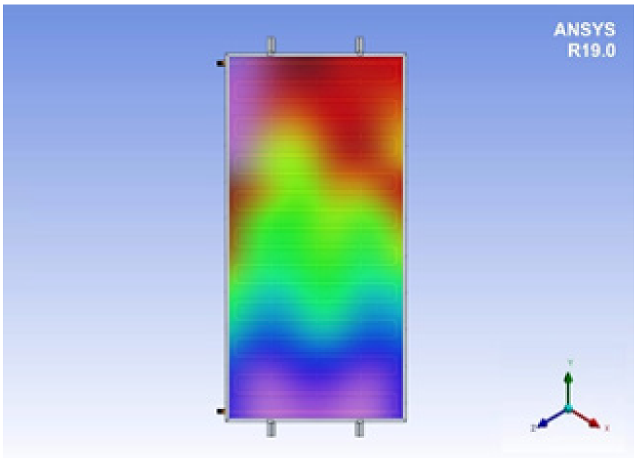

Figure 7: Computational area of the plate of the absorber of the serpentine tube.

Thermal tests of the flat solar collector were carried out during several clear days from January 1 to May 1, 2021.

Figure 8 presents dependence of the thermal pump compressor mass output on steam specific volume of the working substance at absorption. As we see, compressor's mass output increases from specific steam volume at absorption. The higher the working substance steam volume, the higher compressor's performance.

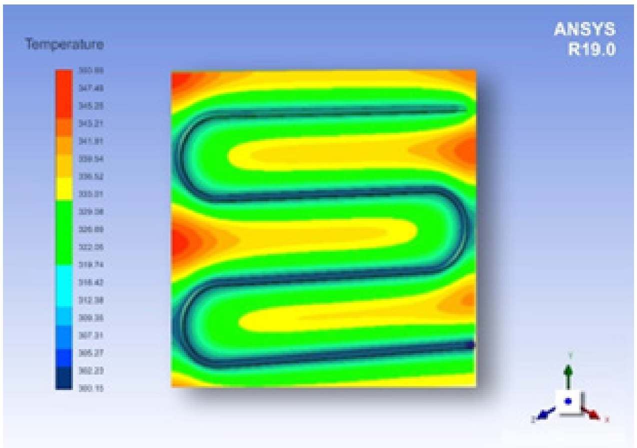

Figure 8: Temperature contours of the plates at an inlet temperature of 30°C.

Figures 9 demonstrate that thermal and material balance of the thermal pump condenser falls in relation to the efficiency and thermal transfer factor of the thermal pump condenser-due to the temperature. It confirms, that the most part of steam (above 99%) condenses in the zone of mass condensation, where penetrates comparably small amount of air. Temperature of saturated steam does not usually exceed 50°C-60°C. In the cooling zone partial steam pressure is less and steam-air mixture temperature is lower. In that zone there is possible the condensate overcooling, which is not favorable for the installation's efficiency in whole.

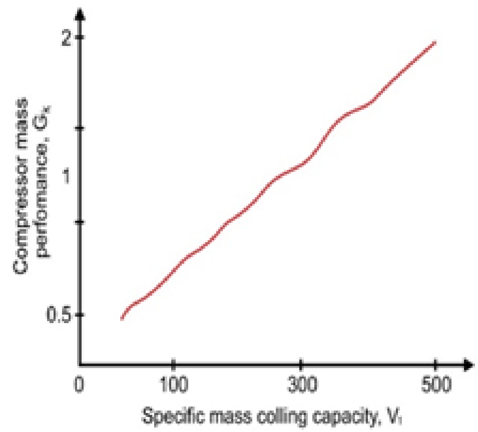

Figure 9: Dependence of thermal pump compressor's mass output on steam specific value of the working substance at absorption.

Figure 10 and Figure 11 shows dependence of thermal balance on the temperature in the thermal pump evaporator. As it is seen from the Figure at water high initial temperature in evaporator there is observed more intense water heating in the condenser.

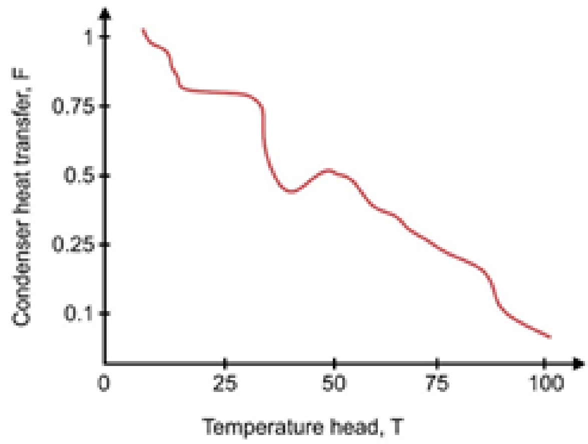

Figure 10: Dependence of heat transfer factor of thermal pump condenser on temperature.

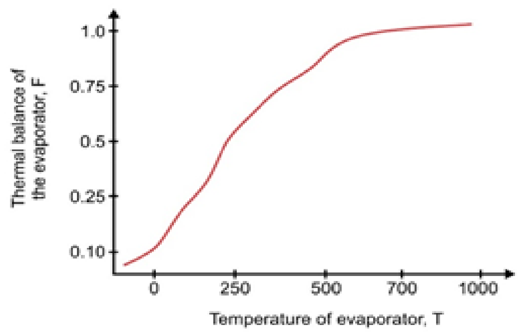

Figure 11: Dependence of thermal balance on temperature in thermal pump evaporator.

Conclusion

The created model was modeled entirely for a solar heating system. On the basis of a mathematical model of a solar flat collector, a block diagram was developed, a block diagram of the collector model. The result of the simulation is the temperature of the fluid leaving the reservoir. A flat solar collector was chosen for the verification; data were collected for 3 months of observation from technical devices. Temperature sensors were installed in the accumulator tank, at the outlet from the flat solar collector, voltage sensors on the pump and vibration. Based on data from sensors on temperature and pressure, we can predict future problems in the installation, such as pump breakdown, depressurization, and more. The difference between the predicted temperature in the model and the actual temperature was observed. This may be a signal that there are deviations from the standard temperature indicators in the system. The model prompts you to inspect the installation. The model also showed abnormal deviations in the pressure (bar) readings in the unit loop. You can also notice large deviations between the predicted values and the original readings from the sensors.

References

1. IRENA (2018) Opportunities to accelerate national energy transitions through advanced deployment of renewables (Report to the G20 energy transitions working group). International Renewable Energy
2. Agency, Abu Dhabi.
3. Niu G (2017) Data-driven technology for engineering systems health management. Springer pp: 1-357.
4. Lui Y, Zhao G, Peng X, Hu C (2017) Lithium-ion battery remaining useful life prediction with long short-term memory recurrent neural network. Annu Conf Progn Heal Manag Soc 9: 1-7.
5. De Keizer AC, Vajen K, Jordan U (2011) Review of long-term fault detection approaches in solar thermal systems. Sol Energy 85: 1430-1439.
6. Ghritlahre HK, Prasad RK (2018) Application of ANN technique to predict the performance of solar collector systems-A review. Renew Sustain Energy Rev 84: 75-88.
7. Kalogirou S, Lalot S, Florides G, Desmet B (2008) Development of a neural network-based fault diagnostic system for solar thermal applications. Sol Energy 82: 164-172.
8. Lipton ZC, Berkowitz J, Elkan C (2015) A critical review of recurrent neural networks for sequence learning. Proc ACM Int Conf Multimed MM 14 :675-678.
9. Srivastava S, Lessmann S (2018) A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data. Sol Energy 162: 232-247.
10. Leva S, Dolara A, Grimaccia F, Mussetta M, Ogliari E (2017) Analysis and validation of 24 hours ahead neural network forecasting of photovoltaic output power. Math Comput Simul 131: 88-100.
11. Correa JC, Cardemil JM, Droguett EL, Behzad M (2019) Assessment of deep learning techniques for prognosis of solar thermal systems. Renew Energy 145: 2178-2191.
12. Kalogirou SA, Agathokleous R, Barone G, Buonomano A, Forzano C et al. (2019) Development and validation of a new TRNSYS type for thermosiphon flat-plate solar thermal collectors: Energy and economic optimization for hot water production in different climates. Renew Energy 136: 632-644.
13. Souliotis M, Kalogirou S, Tripanagnostopoulos Y (2009) Modelling of an ICS solar water heater using artificial neural networks and TRNSYS. Renew Energy 34: 1333-1339.
14. Amirgaliyev Y, Kunelbayev M, Kalizhanova A, Daulbayev S, Auelbekov O (2020) Development of experimental-trial pattern of double-circuit solar installation. 2nd International Conference on Electrical Communication and Computer Engineering (ICECCE) pp: 1-6 .
15. Yedilkhan A, Murat K, Beibut A, Tumur M, Azhibek D (2020) Mathematical justification of thermosyphon effect main parameters for solar heating system. Cogent Engineering 7: 1-13.
16. Amirgaliyev Y, Unelbayev M, Kalizhanova A, Kozbakova A, Aigerim A (2019) Solution of numerical and statistical data and construction of prediction model by means of computer-aided learning program light gbm for solar heat supply «flat solar collector+heat pump» system. J Adv Res Dyn Control Syst 11: 2733-2745.
17. Amirgaliyev YN, Kunelbayev M, Wójcik W, Kozbakova AK, Irzhanova AA (2018) Solar-driven resources of the Republic of Kazakhstan. News of the national academy of sciences of the republic of Kazakhstan, Series of Geology and Technical Sciences 3: 18–27.

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