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Analysis and Simulation of CSP and Hybridized Systems

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Usage of Artificial Intelligence for Prediction of CSP Plant Parameters

Thomas Kraft[1], Mohammad Haziq Khan[1], Gregor Bern[1], and Werner Platzer[1]

[1] Fraunhofer-Institut für Solare Energiesysteme ISE, Germany

Abstract. Artificial intelligence offers the opportunity to use the large amounts of data from commercial CSP power plants to supplement the experience of operations personnel through accurate predictions to optimize predictive maintenance and operations management. As a constant high outlet temperature of the solar field even under fluctuating environmental conditions is a relevant factor for the efficiency of commercial CSP power plants, the focus of this work is on the prediction of solar field outlet temperature. The analysis of this work is based on operating data of the commercial CSP power plant Andasol III in Spain with a temporal resolution of 5 minutes over a period of 5 consecutive years. To optimize the prediction, the three models random forest, feed forward artificial neural network – also known as multiple layer perceptron (MLP) – and long short-term memory (LSTM) network were compared in their performance and optimized separately by means of hyperparameter variation. The best results were achieved with the LSTM model with a mean absolute error of 6.78 K averaged over the prediction period of one year. By using AI models, future deviating outlet temperatures can be predicted at an early stage. These predictions offer the possibility to keep the outlet temperature more constant by predictive adjustment of the mass flow and thus increase the efficiency of the solar field and the whole CSP plant.

Keywords: Solar Field Optimization, Outlet-Temperature Prediction, Concentrated Solar Power (CSP), Artificial Intelligence, Neural Networks, Long Short-Term Memory (LSTM)

1. Introduction

The importance of artificial intelligence (AI) is increasing worldwide. Neural networks are being used more and more frequently both in the private and in the professional environment. The applicability of AI was also increasingly examined in the CSP context, e.g. for the prediction of the outlet temperature of a single collector [1] or the estimation of the energy production of a parabolic trough solar thermal power plant [2]. In this work, the predictability of individual system parameters for the solar field is examined more closely using AI models, focusing on neural networks (NN). A constant and high outlet temperature is one of the key factors for efficient solar field and power block operation. Ideally, all collector loops are adjusted and operated in such a way that they feed the heat transfer fluid (HTF) at its defined maximum operation temperature into the header pipe. Thus, mixing losses are minimized and the maximum storage capacity and power block efficiency is reached.

The focus of this work is the prediction of the solar field outlet temperature in reaction to meteorological and operational data. The improved predictive accuracy is expected to enhance fault detection, improve predictive maintenance, and increase power plant efficiency in the long term.

2. Methodology

This work is based on a data set of five years of operational data from Andasol III, a parabolic trough power plant located in Spain. The plant has a nominal turbine capacity of 50 MW_{el} and an annual yield of more than 150 GWh_{el}, and is supplied with heat from a solar field consisting of 152 loops connected hydraulically in parallel. The time horizon of the examined data is 5 years (2017-2021) with a resolution of 5 minutes.

As the pure amount of measured data in commercial power plants is very high (can succeed 1 GB of raw data per day), only relevant daytime operation data is considered for the prediction to reduce the computing power needed. The considered time span between sunrise and sunset was calculated individually for each day, considering the geographic location (latitude and longitude) of the examined facility. By considering all possible times with relevant DNI, it is ensured that relevant operational data are not excluded from use. A correlation matrix of possible input parameters (among others direct normal irradiation DNI, mass flow and wind speed) was carried out to investigate which of the available parameters have the greatest effect on the variable to be predicted (the outlet temperature). With the resulting parameters, three different common models were tested: random forest, modern feedforward artificial neural network – also known as multiple layer perceptron (MLP) – and long short-term memory (LSTM) model.

2.1 Model Training, Testing and Validation

Following Karunasingha [3], the mean absolute error *MAE*, applied to quantify the error of AI predictions, is defined as follows:

$$MAE = \frac{\sum_{i=1}^{N}\left|T_{\mathrm{meas},i} - T_{\mathrm{pred},i}\right|}{N} \tag{1}$$

where T_{meas} is the measured outlet temperature, T_{pred} is the predicted outlet temperature and *N* the total amount of samples. The model prediction accuracy *MPA* defined in the context of this work also considers the mean of all measured temperatures $\overline{T}_{\mathrm{meas}}$ as follows:

$$MPA = 1 - \frac{\overline{T}_{\mathrm{meas}} - MAE}{\overline{\mathrm{T}}_{meas}} \tag{2}$$

The performance of the different models was evaluated by training them with 3 years of the operational data (60% of available data), testing them with one year of operational data (20% of available data) and validating them with one year of operational data (20% of available data).

2.1 Model Optimization

Each of the implemented models was optimized by systematic and iterative hyperparameter variations. As the random forest is a simple model and there are not many hyperparameters to optimize, the focus in this work is on the NN optimization. The NN models (MLP and LSTM) were optimized via changing systematically the following hyperparameters:

- Architecture Parameters: Number of hidden layers & neurons per (hidden) layer
- Training Parameters: Learning rate (lr) & batch size (bs)

In addition to these hyperparameters, the output sequence (future steps of prediction) and the input sequence (historical steps used for prediction, only for LSTM) were varied to analyse their impact to the model prediction performance.

Figure 1 shows as an example the architecture of a neural network with 10 input features, 5 hidden layers and 128 neurons per hidden layer used in this work to predict the solar field outlet temperature.

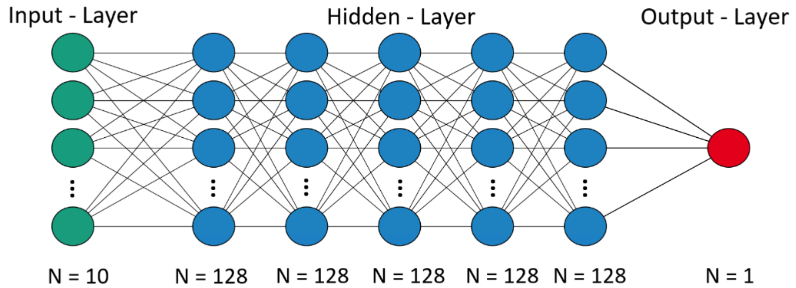

***Figure 1**. Example Scheme of a MLP model for outlet temperature prediction.*

3. Results

In this chapter, the determination of the relevant features (input variables), the comparison of the performance of the different used models and the optimization of the considered NN models via hyperparameter variation are shown.

3.1 Correlation Matrix for Feature Importance Analysis

For the prediction of the outlet temperature, ten features were considered, which include measured data (e.g., DNI, wind, ambient temperature) and calculated data (e.g., incidence angle modifier (IAM) and sun position angles zenith and azimuth). Figure 2 shows the calculated correlation matrix of the outlet temperature and all considered instantaneous input features for this work in the order of decreasing importance. The wind direction is not considered but is just shown as an example for a feature that is not strongly affecting the outlet temperature. By using only 10 input features with the highest correlation to the exit temperature for the AI model training, the required computational power is greatly reduced without significantly affecting the prediction accuracy.

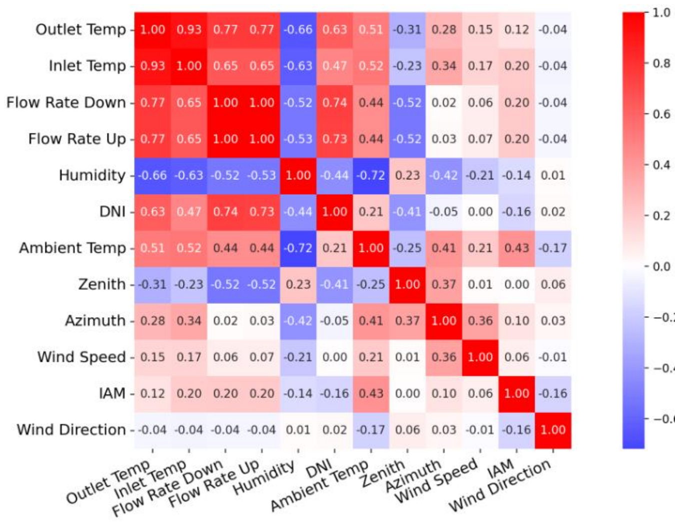

***Figure 2.** Correlation matrix including all features considered in this work and wind direction.*

3.2 MLP Model Optimization

The optimization of the MLP was done on all the hyperparameters mentioned in section 2.1. As an example, Figure 3 (left) shows the result of a sensitivity analysis of the hyperparameter learning rate. For each different learning rate, the correspondent validation loss (indicated the error of the model) is shown over the amount of epoch (NN training steps). The red framed area is shown again on the right – zoomed in for a detailed view. It can be clearly seen, that for very high and for very low learning rates, the validation loss increases. The lowest validation loss and thus the best MLP model performance is reached with a learning rate of 2E-4.

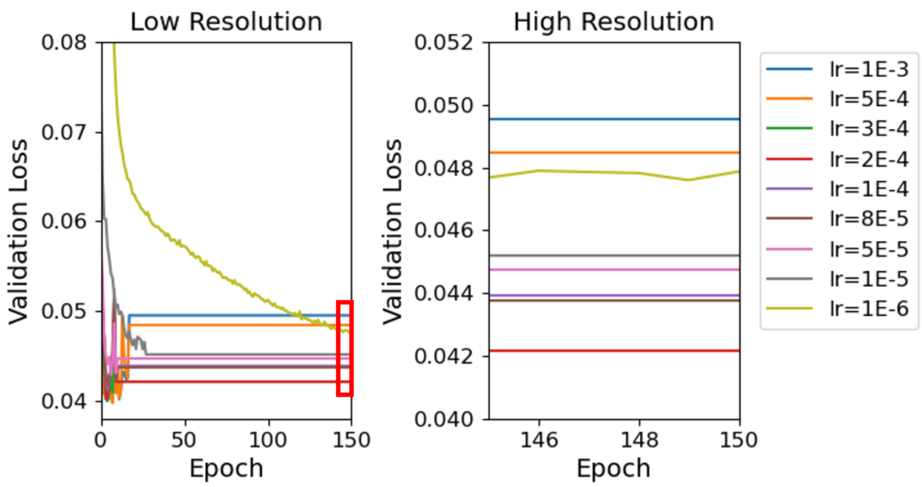

***Figure 3**. Hyperparameter variation of learning rate and its influence on validation loss during all epochs of the trainings process for MLP model – predicting the outlet temperature of the solar field.*

After optimization of the MLP model hyperparameters on the current time step, the model was used to predict the outlet temperature of the solar field for different future time steps. Figure 4 shows the mean absolute error for different future predictions between the current time step and 100 minutes of forecast of the optimized MLP model. It can be clearly seen, that with an increasing time of forecast also the mean absolute error of the prediction increases. During the first 15 minutes the mean absolute error is almost constant. The authors assume that the reason therefore is the physical time offset between the impact of a change in the input features (e.g. decrease of DNI due to clouds) and the measured result on the output sensor (reduced outlet temperature), which is also in the range of 5-30 Minutes depending on the mass flow rate through the solar field.

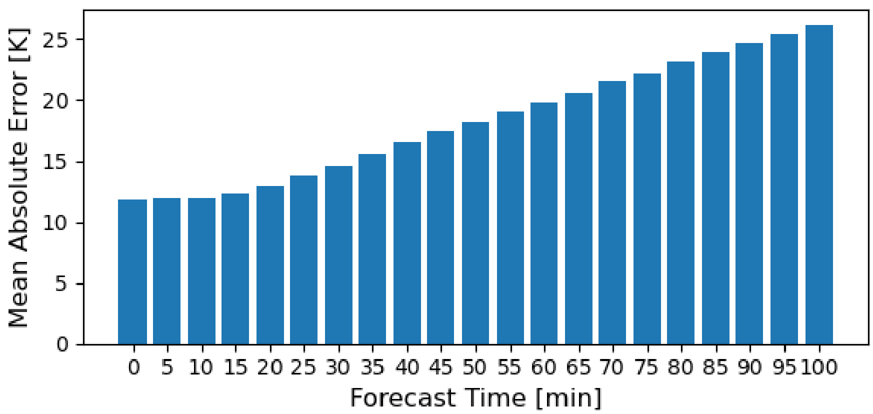

***Figure 4**. Influence of increasing forecast time on the mean absolute error of the optimized MLP model prediction.*

3.3 LSTM Model Optimization

The optimization of the LSTM was also done on all of the hyperparameters mentioned in section 2.1. Equivalent to the MLP model, Figure 5 shows the result of a sensitivity analysis of the hyperparameter learning rate. The red framed area is shown again on the right – zoomed in for a detailed view. As for the MLP model it can be clearly seen, that for very high and for very low learning rates, the validation loss increases. The lowest validation loss and thus the best LSTM model performance is reached with a learning rate of 9E-5.

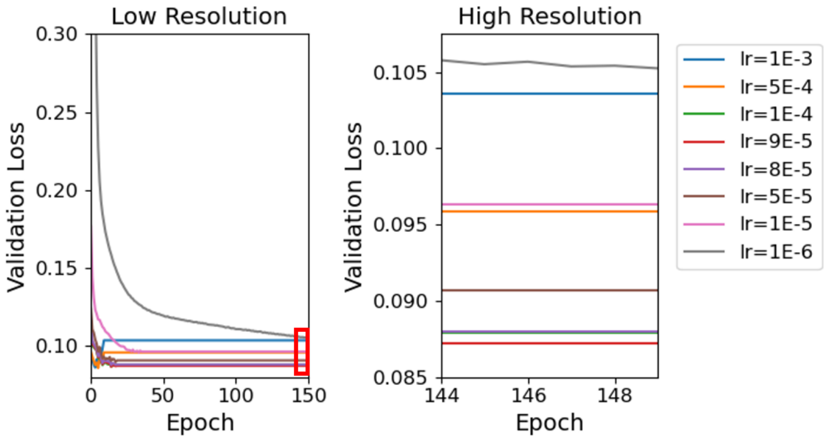

***Figure 5**. Hyperparameter variation of learning rate and its influence on validation loss during all epochs of the trainings process for LSTM model – predicting the outlet temperature of the solar field.*

As described in section 3.2, the effect of forecast time and historical data used for prediction were analyzed. Figure 6 shows the influence of these hyperparameters on the mean absolute error of the prediction. Each color represents a different forecast time. It can be seen again (as with the MLP) that increasing the forecast time results in an increase of the MAE. As described in chapter 2, 25 minutes correspond to a data series of 5 consecutive time steps of the data set, with a time offset of 5 minutes each. The first minutes of historical data have the strongest effect on the MAE – a conclusion that can be drawn from the largest negative gradient. This relevance of the historical data decreases with increasing forecast time. Furthermore, up to an optimum, a larger amount of historical data reduces the MAE. From this optimum on, a further increase in the amount of historical data for training - with otherwise identical hyperparameters - results in an increase of the MAE of the prediction.

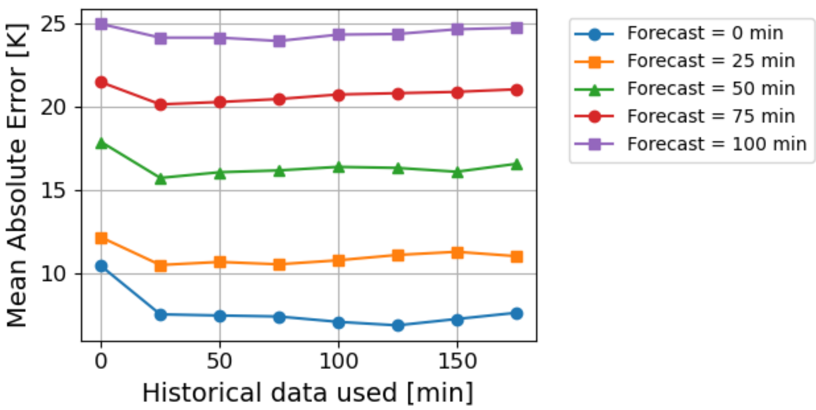

***Figure 6**. Influence of forecast time and historical data use on the mean absolute error of the optimized LSTM model prediction.*

3.4 Comparison of Model Performances

Figure 7 shows the predicted and the measured temperatures of four consecutive days for the three considered models. While on sunny days (day 1 and 2) the outlet temperature can be predicted quite accurately with all models, the deviation between measured and predicted temperature differs especially on days with fluctuating DNI (day 3 and 4). With a MAE of 6.87 K, the LSTM achieves the most accurate predictions. The deviations between measured and predicted temperatures do not show any special systematics, but temperature changes are partly predicted too early, partly too late and partly at deviating temperature levels.

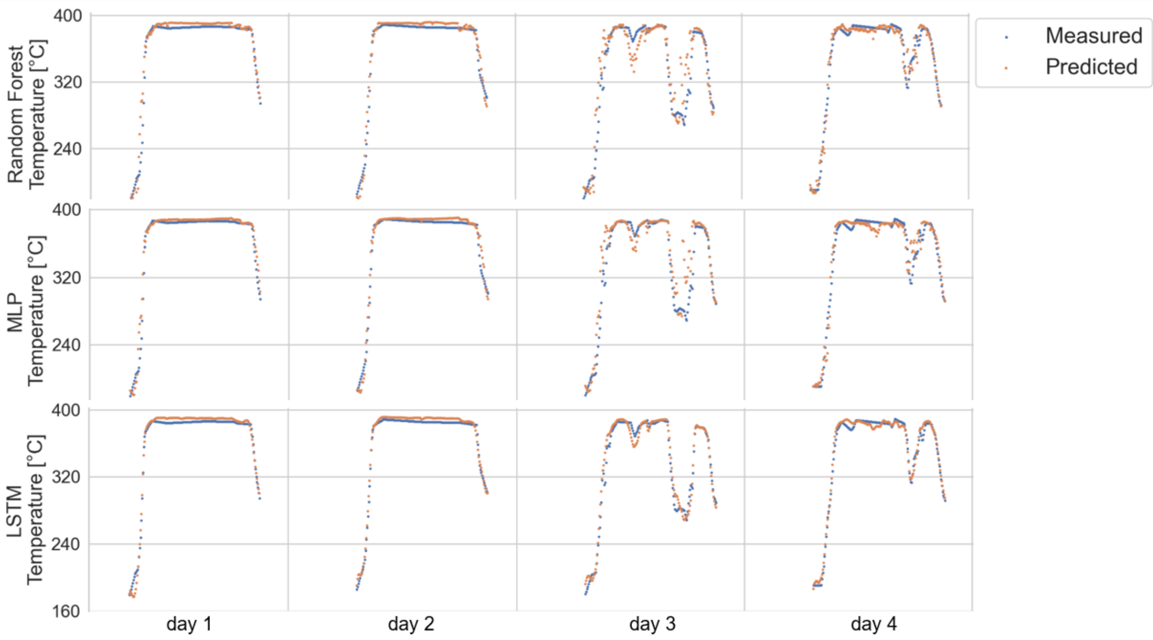

***Figure 7**. Comparison of measured and predicted outlet temperature of the 3 implemented models for four consecutive example days.*

The mean absolute error of the three optimized models as well as the corresponding hyperparameters are shown in table 1.

***Table 1.** MAE and corresponding hyperparameters for the optimized models.*

	Random Forest	**MLP**	**LSTM**
MAE [K]	**10.73**	**11.87**	**6.87**
Nr. of Decision Trees [-]	1000	-	-
Nr. of (hidden) layers [-]	-	5	2
Nr. of neurons per (hidden) layer [-]	-	128	100
Learning Rate [-]	-	2E-4	9E-5
Batch size [-]	-	64	64

With a MAE of 6.87 K, the LSTM achieves the most accurate predictions of the outlet temperature. However, the MAE is not constant over the year, but fluctuates over the months. Figure 8 shows the MAE for all three models by month. Based on the similar relative distribution of the MAE over the year as well as the profiles of individual days with and without significant DNI fluctuations (see Figure 7), it can be deduced that all three models prefer similar framework conditions (e.g. low DNI fluctuations). In February, the mean MAE for the LSTM model was even less than 4 K.

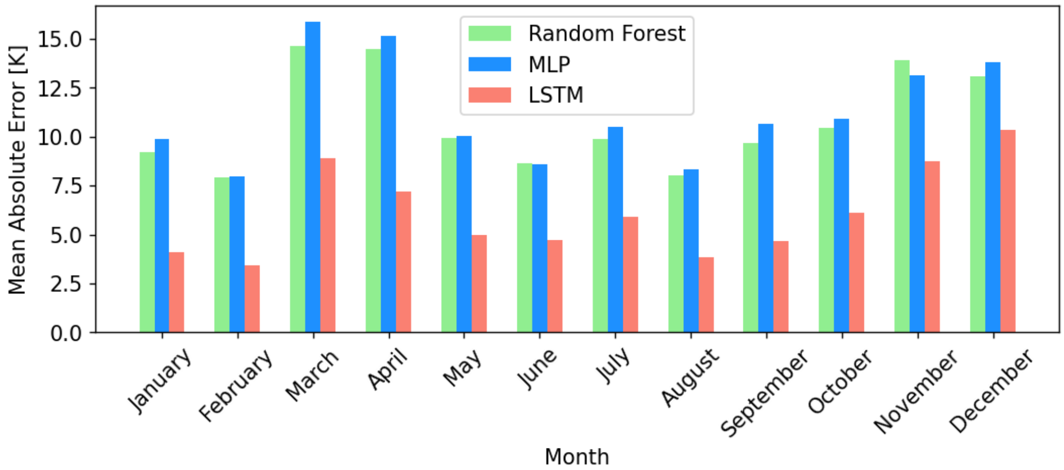

Figure 8. *Monthly mean absolute error of all three implemented models.*

4. Conclusion and Outlook

Within the scope of this work, it has been shown that artificial intelligence can be used to predict individual physical output variables of a CSP plant – in this work the outlet temperature of the solar field. With a mean absolute error of 6.87 over the year, the LSTM model achieved significantly better prediction accuracies than the random forest or the MLP model. In general, the accuracies of the predictions decrease with a higher forecast time for both the MLP and the LSTM model. Due to the physical offset between relevant input data (e.g. DNI on collectors) and the measurement of the output (outlet temperature at the end of the solar field), highest prediction accuracies can be achieved with a forecast time of less than 25 minutes.

Through deeper investigations of the used models with additional data, the performance of the modelled neural networks might be further improved and thus the errors decreased. In addition to the usage of a larger amount of CSP plant operation data (including both longer time intervals and higher temporal and spatial resolution), especially the usage of generated simulation data for AI model training might further improve the prediction accuracy. By using the neural network in combination with good weather forecast data, further improvements may be achieved like earlier detection of an increase in outlet temperature (reduction of dumping) or earlier detection of a reduction in outlet temperature (lower generator efficiency). In the specific case, for instance, if a lower outlet temperature is predicted due to clouds, the mass flow could be reduced in advance to maintain a constant future outlet temperature. During a transitional phase for testing purposes, the AI-powered control system could also provide only an alarm or notification to the operating personnel. This way, the operational responsibility remains with the personnel, minimizing the risk of detrimental operations based on incorrect or unrealistic predictions. Furthermore, this could contribute to strengthening the trust in using AI for operational control. Furthermore, different operating strategies could be tested using correspondent forecast data. By comparing the resulting predictions, the results can be used to generate concrete recommendations to maximize thermal efficiency and thus to optimize the plant operation.

In the case of CSP power plants, even small gains in efficiency result in high financial saving or revenue potential. The outlet temperature of commercial power plants is usually not constant but fluctuates, especially in the case of fluctuating DNI. As a result, early predictive control of the mass flows through the solar field or a warning mechanism to prevent overheating (predictive operation) via usage of AI models is a possible application to reduce the fluctuation of the outlet temperature and thus increase the efficiency of the entire CSP plant.

Data availability statement

The data used in this work comes from third parties. For reasons of confidentiality, they are not publicly accessible.

Author contributions

Thomas Kraft:	Conceptualization, methodology, project administration, Supervision, Validation, Writing – original draft
Haziq Khan:	Data curation, Formal analysis, methodology, Validation, Visualization, Writing – review & editing
Gregor Bern:	Funding acquisition, project administration, Supervision, Writing – review & editing
Werner Platzer:	Supervision, Writing – review & editing

Competing interests

The authors declare that they have no competing interests.

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