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Forecasting Electricity Generated in A Rankine Power Station Running in Grid-connected Mode

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Abstract: To ensure proactive and intelligent control of the electrical power generated in industrial units self-producing energy, the construction of a data-driven model devoted to power prediction is an efficient solution that we have proven in this contribution. The remarkable added value of the paper was articulated around three main pillars: primarily, we have modelled a power station based on Rankine cycle that serves the energy needs of an industrial facility. Secondly, the connection of this plant to the public electric grid has been taken into consideration in modelling. Thirdly, we have used the model to avoid paying unwanted bills thanks to the forecasting of periods when there is an energy importation from grid. Before constructing the model, we have prepared a dataset composed of more than 25 million data points, reflecting the history of 3 years of archived data related to fifteen 15 features, in order to predict the target variable of this study. After finding that GRU and LSTM are among the most successful deep learning algorithms in energy prediction, we decided to use them in our particular application. Afterwards, a comparative study between them was first carried out on accuracy, where encouraging results were obtained on both sides, with respective scores of 98.73% and 99.36% during the training step, followed by 98.51% and 99.11% during the testing phase. Besides, the evaluation in terms of loss functions gave a convergence of the GRU model after 8 epochs, against 11 epochs for the LSTM algorithm. Therefore, we preferred to use LSTM in the definitive model because of its higher accuracy, providing that good computing power is used, so that the processing time could be acceptable by the end-users. Finally, we deployed the model to simulate a real case of forecasting the power drop one week in advance. In this case, we found that if the industrial unit had used the results of the model as a proactive decision support tool, it would have avoided importing 1456.4 MWh for 8 days from the national grid, which was equivalent to a loss of 119,094.8 USD.

Keywords: Electrical power forecasting, Deep learning, Power station, Rankine cycle, Industry 4.0.

1. Introduction

The production of electrical energy in power stations has always been a capital concern for the industrial community working in the energy sector, especially when it comes to ensuring a high level of service continuity for the consumers. In this sense, Artificial Intelligence-based modelling has become a key technology of industry 4.0, to be used for supporting the management and the business steering of these vital infrastructures.

In the present work, we will be interested in building a model that uses deep learning algorithms in order to predict the future electrical power variations produced in a power plant, through the valuation of the archived data related to its process parameters. Indeed, the aim here is to support decision-making, with a view to considering the best possible mid-term scenarios of energy production.

Moreover, this study brings a novelty that combines three key ideas:

The first one concerns the modelling of a specific

Table 1. Summary of some most recent research works

Ref	First author	Year	Field of energy prediction	Used Machine Learning techniques	Advantages and drawbacks of the used techniques
[1]	Dhari	2021	Wind Power	DPSO. BPNN.	Merging the two Deep Learning algorithms in one solution has permitted to enhance the accuracy of the model to exceed 98%. The drawback of DPSO is the sensitivity to new parameters. Adjusting additional settings can be tricky and requires extensive testing and fine-tuning.
[2]	Heydari	2021	Wind Power	Fuzzy-GMDH optimized by Grey Wolf.	Real application of the model results in a wind farm in Sweden. The optimizer Grey Wolf has permitted to give higher accuracy. The inconvenient of fuzzy settings can be trickier to adjust than traditional settings. Their adjustment requires specific expertise in fuzzy logic.
[3]	Shohan	2022	Electrical Load	LSTM-NP.	The hybrid algorithm has rised the accuracy of the model for load forecasting over the other techniques. LSTM-NP disadvantage is the overfitting if the model is too complex for the amount of available training data.
[4]	Al Rayess	2021	Hydraulic Power	DT. GL. GBT. RF.	All the four techniques tested have given approximatively similar results, with a maximum accuracy of 72%, which is a disadvantage because there is some other techniques that have more higher scores.
[5]	Abu-mohsen	2023	Electrical Load	LSTM. GRU. RNN.	To predict electrical loads, the GRU model has recorded the best score that exceeds 90.2%. Après avoir utilisé LSTM et GRU, the disadvantages of RNN have been eliminated, in particular that of the short memory.
[6]	Liu	2021	Wind Power	CNN.	The constructed model has been applied successfully on a wind farm in China. The use of a dataset containing the four seasons of the year has participated in this success. The drawback of CNN is that the adjusting of its parameters may require experimental trials and adjustments.
[7]	El Filali	2022	Electrical Load	GRU. LSTM.	To forecast the electrical demand in the studied industrial unit, the result has exhibited that GRU is slightly more suitable method versus LSTM. Nevertheless, the use of LSTM did not show any remarkable disadvantage compared to GRU.
[8]	Sabri	2021	Solar Power	BLSTM. CNN.	The results show that the hybrid solution between the two techniques has the lowest error MSE of 0.0089. The use of CNN only struggle to process unstructured data like the tabular one.
[9]	Khan	2019	Wind Power	ARIMA. SVM.	This study is distinguished by the use of a historical data of 17 years, which contributes to the reliability of the model. With the deployment of ARIMA, the author found difficulties in dealing with the seasonal aspect of the data, which paves the way for the need to use Seasonal ARIMA in a future work.
[10]	Saleel	2021	Combined cycle	ANN. DNN.	With a single intermediate layer, the precision score was equal to 94% during the testing phase. The score found can be further improved by using other neural networks such as GRU and LSTM.

[11]	Qianqian	2023	Solar Power	CEEMDAN. LSTM. WGAN.	Comparison between three models basing on a dataset that covers all the four seasons of the year. That element has fostered a good learning of the model, and gave encouraging results about the prediction, but it requires generally more iterations in order to ameliorate the accuracy score.
[12]	Hangxia	2021	Solar Power	LSTM. MLP. ALSTM.	A model that contains a combination of deep learning models by including the attention mechanism and a large number of input factors that enhance the trustability of the model. In deep networks, it was found that the learning of MLP is relatively slow compared to LSTM.
[13]	Serrano Ardila	2022	Solar Power	WFTS. FIG-FTS.	Short-Term solar power Forecasting with an advantage to the hybrid technique regarding performance score. These fuzzy algorithms may require expertise in both machine learning and fuzzy set theory.
[14]	Viscondi	2021	Solar Power	SVM. ANN. ELM.	The dataset is about more than 19,300 daily records registered between 1962 to 2014 including ten meteorological variables, using several machine learning models. That factor of long time period helps to have very good predictions since the model has learned the different situations of all the 52 past years.
[15]	Ming-Ta Yang	2021	Solar Power	LSTM. MLP.	Comparison between 2 models by using raw data inputs of two geographically separated PV systems belonging to different countries, which have the same tropical climate. Regarding the size of the dataset used, there weren't really any particular complexities perceived in the training for LSTM and MLP.
[16]	Ameema	2020	Electrical Load	ANN. SVR. LR. RF. GBRT.	Using five machine learning algorithms, each with its own internal architecture, with a number of 24 million rows and 30 feature parameters, so that to increase the credibility of the model. The observed limitation lies in the slow learning, given the high number of data points.
[17]	Shohan	2022	Electrical Load	LSTM-NP.	Estimates daily peak load consumption a year ahead. That ensures a permanent tracking of the load variations that may occur, especially during the high demand periods. Referring to the score obtained as well as the treatment time, no significant drawback was observed.
[18]	Ciechulski	2021	Electrical Load	LSTM.	The numerical experiments were performed for two types of data (data of the whole country Polish Power System) and a small region of a power system in the country. To improve the training time, a more powerful computing machine is required.
[19]	Bendiek	2021	Solar Irradiance	SVM. FP.	The techniques give the possibility to have both short-term and long-term predictions. The further we go into future time, the worse the prediction will be.

[20]	Sabri	2022	Photovoltaic Power	LSTM. GRU-CNN.	Using several models for short term predictions. Their performances are very close to each other. No disadvantages were recorded in short-term testing.
[21]	Elsaraiti	2022	Solar Power	LSTM. MLP.	Making a half-hour forecast for the next day. As a result, that gives very credible future prediction. The score obtained by LSTM is slightly higher than that of MLP.
[22]	Sharma	2022	Photovoltaic Power	LSTM. ARIMA. SARIMA.	Using statistical and deep learning algorithms with different optimizers, by considering the seasonality variation of data. The disadvantage of LSTM and ARIMA was seen in their inability to handle seasonal data.
[23]	Ameur	2022	Hybrid Solar & Wind	DQLN.	Considering a dataset that combines the input parameters of both solar and wind energy to predict output electrical power. DQLN needs improvement in its testing process to get faster prediction results.
[24]	Mazin	2023	Electrical Load	ANN. GA. ANFIS.	Trying to prove that ANFIS Deep Learning technique, which is based on Neural Network supported by a Fuzzy Logic layer, it gave results slightly better than just using neural networks in predictions.
[25]	Mansoor	2021	Electrical Load	ARIMA. LSTM. RF.	Using the results of ARIMA, LSTM, and Random Forest to validate and compare the accuracy of the new suggested technique, named PVS '*Past Vector Similarity',* with above traditional techniques. Surely, the accuracy found by PVS is better, but it must be confirmed by using a bigger dataset.
[26]	Morad-zadeh	2021	Heating and Cooling electrical Loads	KNN. ENR. BPNN. GRNN. PLSR. SVR.	The studied dataset consisted of 768 simulated buildings, each with eight characteristic properties. Introducing a variety of energy forecasting models for residential and non-residential buildings and assessed the performance of each. The target was the forecasting of CL and HL of the residential building.
[27]	Manh-Hai	2021	Electrical Load	SSA. WT. LSTM. BPNN.	The used short-term prediction approach allows to have a fast reactivity in decision-making, particularly that the performance of the built model is high. When the prediction switch in long-term mode, we remark that the accuracy decrease and the decision-making will be distorted.

[28]	Khizir	2021	Photovoltaic Power	LR. PR. MLP. RFR. DTR. SVR. LSTM.	Providing a state of art on short-term and long-term forecasting of photovoltaic power, with a comparative analysis between the different existing algorithms. Compared to other algorithms used, LSTM was the most relevant technique, especially when we talk about the size of the data, and also the loss functions that converge after less epochs than others.
[29]	Theocha-rides	2021	Photovoltaic Power	BNN. SVR. RT.	Presenting a methodology to predict one day-ahead PV production. A comparative study between some of broadly used machine learning techniques so as to assess their efficacy for the applications of PV power forecasting. The limitation found in Bayesian method is that it needs more computation time, especially when the dataset has been enlarged.
[30]	Tziolis	2023	Electrical load fed by solar system	BNN. SPPT.	Carried out of combining neural network with Bayesian inference, by applying the statistical technique (SPPT: *Statistical Post-Processing Techniques*) to the suitable derived BNN model. The result shows the improvement of the prediction performance of the model, but to deal with SPPT technique, the user must master statistical principles, so as to be able to do hyper-parameters tunings.

kind of industrial power plants called "Rankine-cycle", that relies on a closed thermodynamic process based on four transformations of water and steam, leading to a continuous production of electricity by means of a turbo-generator of 50 Megawatts.

The second novelty concerns the case of modelling where the power station is connected to the electrical public grid, where exchanges of energy are contractually formalized, so that the industrial plant could inject the exceeding energy in the grid, and import it in case of energy deficit.

The third idea is about forecasting the future electrical production of the generator, in order to know if the station will be exporting or importing energy from the grid. This predicted information will help the industrial managers to react previously on process parameters, so as to avoid serious financial losses caused by undesirable energy bills.

To achieve this goal, the contribution of this work is structured to include the following parts:

- Section 2, presents a state of the art on the techniques previously used by scientific researchers to predict electrical energy in different kinds of power plants, followed by the statement of the problem linked to our paper, by selecting the most relevant algorithms that suits our application.
- Section 3, exposes the materials and methods that we have employed to develop the model of forecasting, by starting with a theoretical framework of the case study.
- Section 4, highlights the results related to the training and testing steps of the algorithms used, by making a comparison between their performances, and selecting the suitable one for the targeted model.

This part discusses also the benefits and the impact of findings in terms of reducing the energy bill.

2. Analysis of the recent related works

The target behind elaborating this research survey is to select the most pertinent machine learning techniques that could serve our modelling application. In this sense, a great deal of research has been carried out in the field of electrical energy modelling. Then, we will focus our interest on the modelling techniques at the level of various kinds of energy plants used.

With this in mind, the following Table 1 summarizes some of the most recent scientific research works, with the main advantages and drawbacks in each application:

Through the analysis made on the work carried out recently in this field, it turned out that the common point of convergence was to find the best algorithm to solve their regression problems, essentially linked to the prediction of the electrical energy.

This objective was achieved by the majority of the researchers through the comparative studies done between machine learning techniques, by calculating the mathematical evaluation metrics and interpreting

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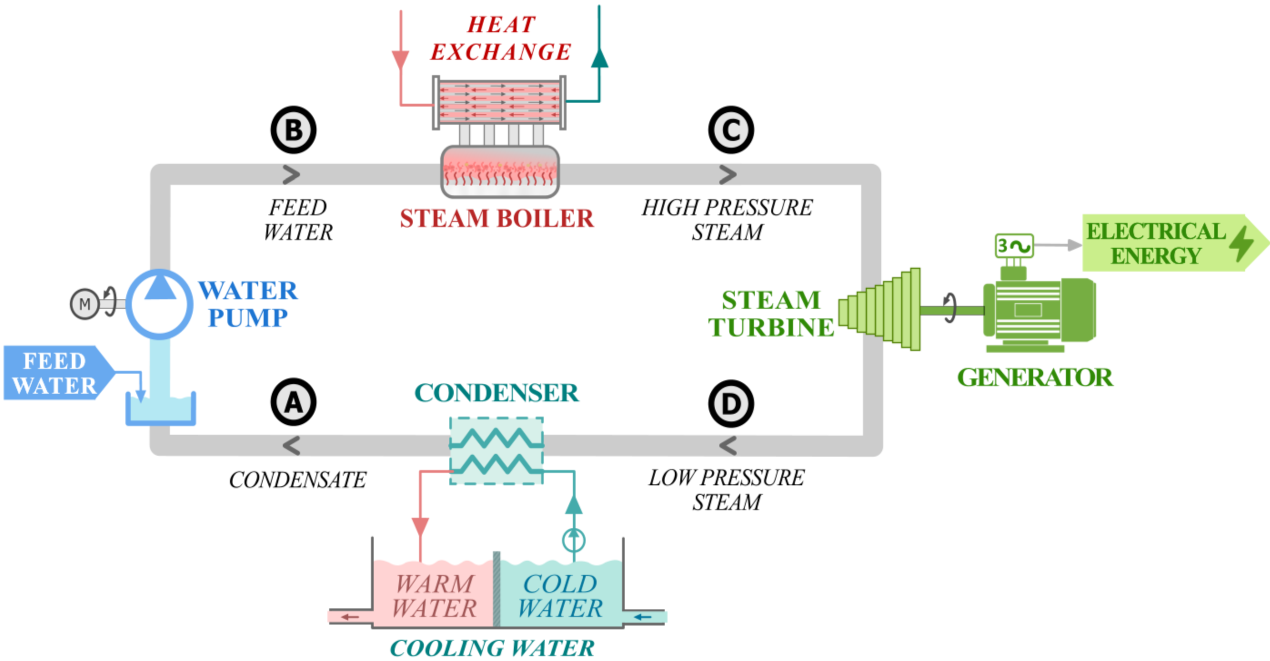

Figure. 1 Studied Rankine cycle showing the steps leading to produce electrical energy

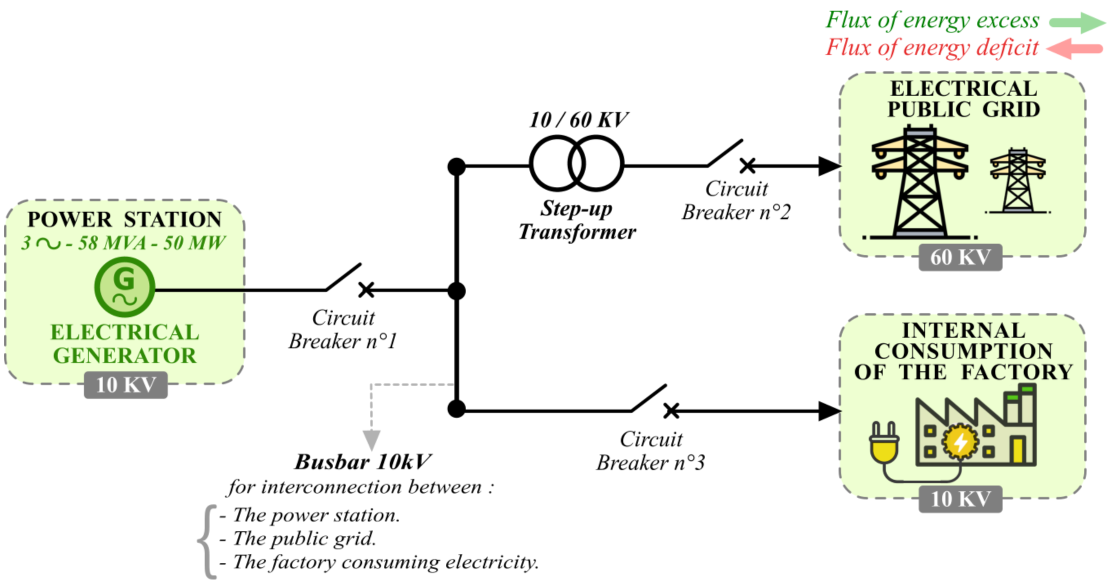

Figure. 2 Interconnection of the power station with the electrical grid to supply the energy needs of the factory

loss functions behaviors, then searching the algorithms with highest accuracy rate with lowest error margins.

Regarding our position toward the research survey, we have decided to select GRU and LSTM algorithms to build our analytical model of forecasting, by doing a comparative study between them.

Our choice is justified by their belonging to the deep learning techniques that guarantee the possibility to do future forecasting of the target variable. Additionally, these models have proven their efficiency in the previous studies either in terms of loss functions or in terms of accuracy score.

Their drawback is limited only in the calculation capacity of the processing machine because of the huge number of data points to be valuated (*more than 25 millions*). Fortunately, this constraint has been overcome by making available a powerful machine in the lab, which will be able to learn and test the model.

3. Materials and methods

3.1 Case study description

It is based on the physical concept of Rankine cycle which marks the process of the steam power plant.

Rankine model is founded on a closed

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thermodynamic cycle composed of four 4 transformations and four 4 equilibrium states, that are annotated: (A), (B), (C) and (D) in Fig. 1.

The principle of each transformation is described hereby:

- Step from (A) to (B): we have an ***«Adiabatic Compression »,*** through the water pump so as to obtain the feed water under high pressure.
- Step from (B) to (C): there is an «***Isobaric Vaporization*** », via the steam boiler. The target is to produce the steam under high pressure, that could be able to train the turbine and generate electrical power in the alternator.
- Step from (C) to (D): the transformation is and ***« Adiabatic Expansion »***, accross the turbine, where we get the steam under low pressure at the output.
- Step from (D) to (A): is the last step of this closed cycle. It is an ***« Isobaric Liquefaction »*** that allows to convert the steam into water, using a condenser and cooling water,

Moreover, the power plant was being studied in the context that it is owned by an industrial plant, and it could produce up to 50 MW.

Similarly, and as described in (Fig. 2), it is made to satisfy the two following energy needs:

- The supply of internal consumers belonging to the industrial plant to which this power station is devoted, which have a nominal power demand of 33 MW.
- The transfer of the electricity excess to the public grid. And of course, the reception of energy from the said grid to satisfy internal consumption in case of a production deficit.

These operations of transfer and reception are realized at the level of the electrical busbar that materialize the connection between the plant and the power grid.

The flow directions of energy are represented in the excess case by the green arrow, and in the deficit case by the red arrow. (Fig. 2)

3.2 Theoretical frameworking

Before starting the modeling part, it is necessary to set the theoretical foundations of the operating mode in the station, as well as its connection with the grid.

This step will be very helpful in identifying the key operating parameters, that could facilitate the definition of the modeling dataset.

3.2.1. Theoretical principle of Rankine power station

We apply the first law of thermodynamics on each machine of Rankine cycle [31]:

$$W + Q = \Delta U + \Delta E_k + \Delta E_p \tag{1}$$

Considering the hypothesis that variations of kinetic (E_k) and potential (E_p) energies could be neglected for this thermodynamical system [32], the equation becomes:

$$W + Q = \Delta U \tag{2}$$

The mass flow rate ($\dot{m}$) in Rankine cycle is a parameter that varies throughout the cycle, that is why it is necessary to include it in the equation:

$$\dot{w_{ij}} + \dot{q_{ij}} = \dot{m_{ij}}.\Delta h_{ij} \tag{3}$$

We now apply this physical equation on the four steps of the process described in the previous part, knowing that states “i” and “j” are exactly the steps (A), (B), (C) and (D).

The following (Table 2) summarizes the four retained equations after this explanation:

We note that by knowing at least two values among the following three: Pressure, Temperature and Volume, it is possible to plot the evolution curves of the transformations. [33]

These curves are three in number, and they are as follows: “Clapeyron Diagram” which represents the Pressure as a function of the Volume (Fig. 3), the

Table 2. First law of thermodynamics applied on the four Rakine cycle transformations

Steps	Transformation nature	Equations
From (A) To (B)	Adiabatic ($\dot{q}_{AB} = 0$)	$\dot{w}_{AB} = \dot{m}_{AB} . (h_B - h_A)$ (4)
From (B) To (C)	Isobaric ($\dot{w}_{BC} = v.\Delta p = 0$)	$\dot{q}_{BC} = \dot{m}_{BC} . (h_C - h_B)$ (5)
From (C) To (D)	Adiabatic ($\dot{q}_{CD} = 0$)	$\dot{w}_{CD} = \dot{m}_{CD} . (h_D - h_C)$ (6)
From (D) To (A)	Isobaric ($\dot{w}_{DA} = v.\Delta p = 0$)	$\dot{q}_{DA} = \dot{m}_{DA} . (h_A - h_D)$ (7)

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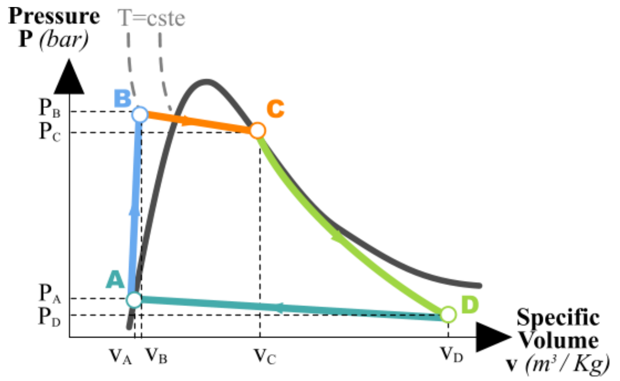

Figure. 3 Clapeyron diagram of Rankine cycle

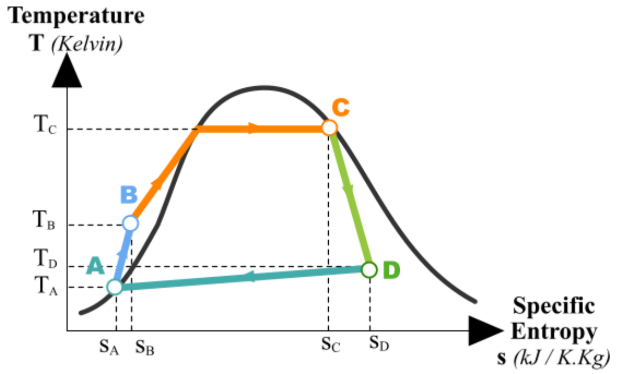

Figure. 4 Entropic diagram of Rankine cycle

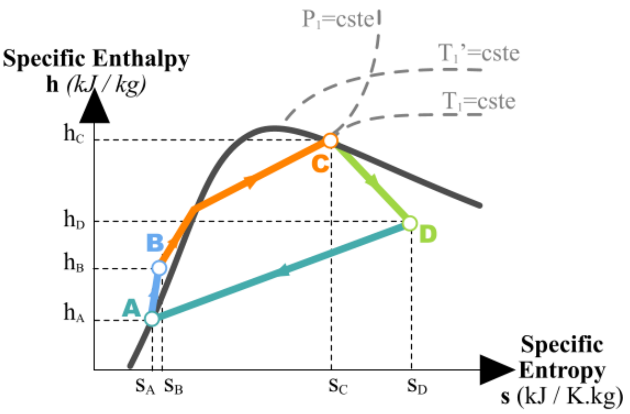

Figure. 5 Mollier diagram of Rankine cycle

"Entropic Diagram" which displays the Temperature as a function of the Entropy (Fig. 4), and "Mollier Diagram" which allows to know the Enthalpy according to the Entropy (Fig. 5).

Indeed, enthalpy and entropy are two physical quantities that can be deduced from the thermodynamic tables of water and steam. [34]

3.2.2. Theoretical principle of the electrical connection

The theoretical aspect of the interconnection between the 3 parts constituting our electrical network is based on the exchange of energy. This exchange can be seen in Boucherot's theorem [35], which states that:

«For a sinusoidal alternating electrical network where all the quantities are of the same frequency, the total active power is the algebraic sum of the active powers of each receiver. The same is true for reactive power, but not for the apparent power which is equal the vector sum of the true power and reactive power ». [36]

In other words, this theorem expresses simply the conservation of power in a network, where the sum of the active powers received by the consumers is equal to the sum of those supplied by the generators.

In our case, and as a sign convention, we have:

- The power station always acts as a "generator" of energy (P_{gen}).
- The internal factory always acts as a "receiver" of energy (P_{int}).
- The electrical grid as a "receiver" in the event that the plant is in excess of energy, and acts as a "generator" when it is in deficit of energy (P_{grid}).

Consequently, Boucherot's theorem is expressed for active power like this:

- In case energy excess:

$$P_{gen} = P_{int} + P_{grid} \tag{8}$$

- In case of energy deficit:

$$P_{gen} + P_{grid} = P_{int} \tag{9}$$

3.3 Construction of the dataset

To construct a good dataset that could give a trustable model of power prediction, its parameters must provide information on each stage of the energy production at the power plant.

That's why we have defined the main criteria to select the suitable features of the dataset:

- Criterion n°1: parameters that describe the evolution of each transformation (A—B), (B—C), (C—D) and (D—A).
- Criterion n°2: parameters that describe the states of equilibrium (A), (B), (C) and (D).
- Criterion n°3: main electrical parameters describing the connection with the electrical grid.

3.4 Data acquisition method

In the industrial context, to acquire the defined data, several architectures are possible. The key is to make a transition from the operational technology

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Table 3. Parameters selected for the dataset

	Criterion of selection	Physical parameter	Symbol	Unit	Nature
1	n°1	Mass flow (A→B)	$\dot{m}_{AB}$	t/h	Feature
2		Mass flow (B→C)	$\dot{m}_{BC}$	t/h	Feature
3		Mass flow (C→D)	$\dot{m}_{CD}$	t/h	Feature
4		Mass flow (D→A)	$\dot{m}_{DA}$	t/h	Feature
5	n°2	Pressure (A→B)	P_{AB}	bar	Feature
6		Temperature (A→B)	T_{AB}	°C	Feature
7		Pressure (B→C)	P_{BC}	bar	Feature
8		Temperature (B→C)	T_{BC}	°C	Feature
9		Pressure (C→D)	P_{CD}	bar	Feature
10		Temperature (C→D)	T_{CD}	°C	Feature
11		Pressure (D→A)	P_{DA}	bar	Feature
12		Temperature (D→A)	T_{DA}	°C	Feature
13	n°3	Busbar voltage	U	Volts	Feature
14		Busbar power factor	P_f	-	Feature
15		Frequency	f	Hz	Feature
16		Active Power of the generator	P_{gen}	MW	Target

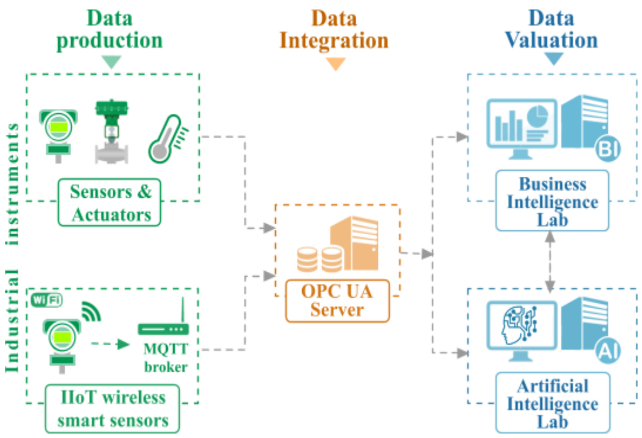

Figure. 6 Proposed architecture for data acquisition

(OT) network to the information technology (IT) one. [37]

We proposed an architecture based on three layers (Fig. 6). The first is related to the data generation through industrial measuring instruments, integrating Industry 4.0 technologies like IIoT devices *(Industriel Internet of Things).* The second layer is that of data integration. The third component is that of data processing, based on interaction between the maching learning model development servers, as well as those of business intelligence (BI) to create dashboards that allow to track the results of the model in real time, including there are future forecasting curves.

3.5 Considered algorithms in power station modelling

As we are dealing with continuous variables in the dataset, the algorithms to be chosen must be devoted to resolve a problem of regression. Moreover, all the variables are annotated, which requires also to use algorithms belonging to the category of supervised machine learning.

According to the studies done in the previous research works, we had a wide choice of algorithms to use because of their suitableness to our application. Finally, we opted for two algorithms based on recurrent neural networks (RNNs), which constitute a cornerstone in deep learning techniques.

More precisely, we had chosen two improved versions of the RNNs, which are LSTM (long short-term memory networks) and GRU (gated recurrent unit). Indeed, these algorithms made it possible to overcome the problems of exploding and vanishing gradients that appeared in the classical RNN.

3.5.1. Long short-term memory (LSTM)

The internal structure of every cell based on the LSTM algorithm contains three gates: the input gate, the forget gate, and the output gate, as shown in the architecture (Fig. 7).

These gates control the flow of data inside the cell of LSTM, allowing it to retain, forget, or generate new information. [38]

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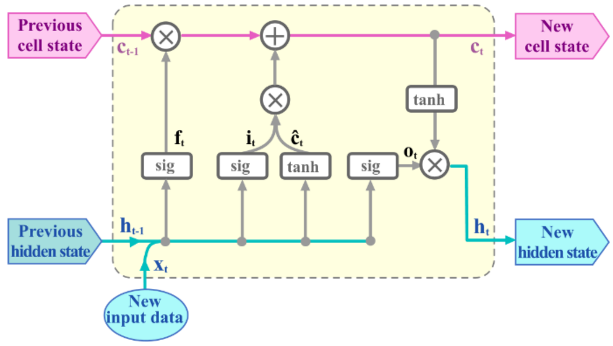

Figure. 7 Internal structure of LSTM cell

- *Forget gate* ***(f_t)****:*

It defines how much anterior data must be dropped from the cell state. It takes into account the actual input and the antecedent invisible state to produce an activation vector between 0 and 1 for each component of the cell state. The values that are nearing 0 marks information to be forgotten, while the values close to 1 give data to be kept.

- *Input gate* ***(i_t)****:*

It checks how much new data must be appended to the state of the LSTM cell. It takes into account the actual input and the anterior unseen state to calculate an activation vector between 0 and 1 for each component of the cell state. The values that are nearing 0 marks information to be forgotten, while the values close to 1 give important data to be kept.

- *Output gate* ***(o_t)****:*

This third gate verifies the amount of information to be sent out of the LSTM. It takes into account the actual input value and the antecedent unseen state to produce an activation vector between 0 and 1 for each component of the cell state. This activation vector is then multiplied by the output of the cell's activation function to produce the final output.

3.5.2. Gated recurrent unit (GRU)

GRU neural networks are designed to get temporal links in the sequences of data. [39] Their internal structure is similar to LSTMs, but it is more simplified with only two gates to control the flow of information within the cells. (Fig. 8)

- *Reset gate* ***(r_t)****:*

It determines how the antecedent state should be combined with the current input. It takes into account the actual input and the anterior invisible state to give an activation vector between the values 0 and 1. This vector is then used to reset the previous hidden state, indicating which elements of the antecedent state must be ignored or updated.

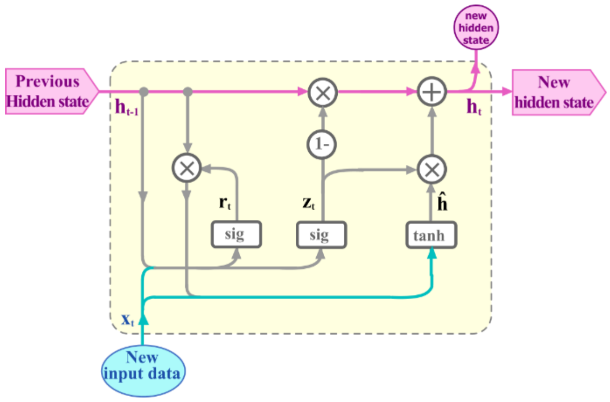

Figure. 8 Internal structure of GRU cell

- *Update gate* ***(z_t)*** *:*

It determines how much the different information should be kept in the hidden state. It takes into account the actual input and the previous hidden state to produce an activation vector between 0 and 1. This vector is then used to combine the actual input with the previous invisible state, controlling the amount of information to keep.

4. Results and discussion

To animate the model using the aforesaid algorithms of deep learning, we opted for a dataset of sequential data belonging to the archived history of an industrial unit.

The duration considered is three 3 years, beginning from 01-June-2020 until 31-May-2023, with a sampling period of one 1 minute. In other terms, we have used a data volume of 1,581,120 data points for each of the 15 features and the target, which means that we dealed with more than 25 million data points for the whole dataset.

Similarly, we relied on the Python language in the modeling, where we used "*Spyder*" as the development environment, which belongs to the "*Anaconda*" distribution.

We note also that we have splitted the constructed dataset into two parts. Indeed, the first part called "Training Set" constitutes 80% of the dataset, while the second part called "Testing Set" contains 20% of the data volume.

4.1 Results in terms of loss functions

The loss functions provide information on 2 things: the learning capacity (*underfitting /overfitting*), and the speed of convergence (*processing time*).

To monitor the progress of the model and detect the possible problems of overfitting or underfitting, it was necessary to generate the loss curves after the deployment of each algorithm, using the mean square

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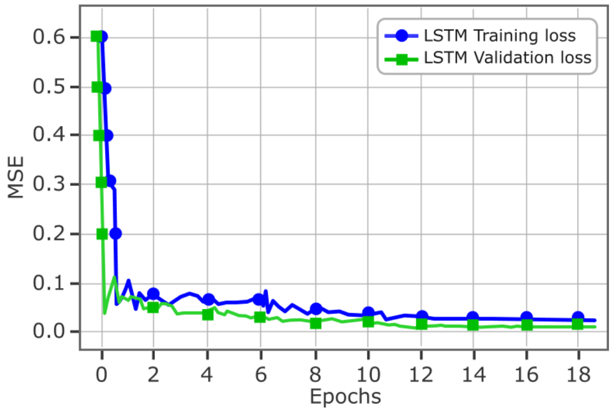

Figure. 9 Obtained loss functions of LSTM algorithm

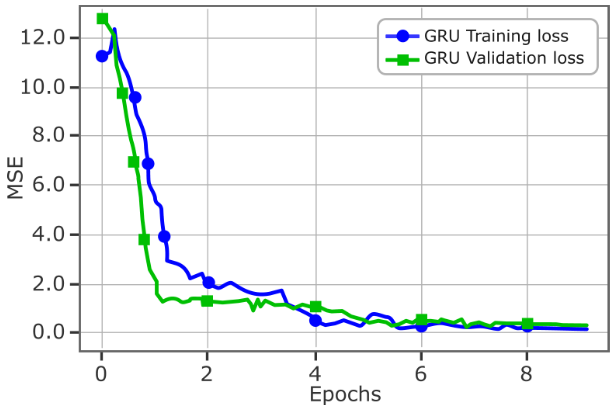

Figure. 10 Obtained loss functions of GRU algorithm

Table 4. Performance metrics obtained

	LSTM		GRU	
	Training step	**Testing step**	**Training step**	**Testing step**
R²	0.9936	0.9911	0.9873	0.9851
MSE	0.00024	0.0003	0.0002	0.0029
RMSE	0.0154	0.0173	0.0141	0.0538
MAE	0.0031	0.00435	0.0061	0.0248

error (MSE) as a function of the number of epochs performed by the LSTM and GRU algorithms. [40]

Whether in the training phase or in the test phase, the shape of the loss curves was gradually decreasing, epoch after epoch, so that the error was stabilized at a minimum towards the end of the iterations.

The LSTM loss curve stabilizes and becomes almost zero after the 11th epoch. Similarly, we noticed that the curve has less noise during the test phase, which is a sign of good learning that will allow the model to be able to generalize successfully the learning process on new data.

The major observation raised after the deployment of the GRU algorithm is that it converges from the 8th epoch, slightly faster than LSTM, although it begins learning with a larger error. Indeed, its error required fewer epochs to converge towards the zero. We also note that GRU stabilizes at a higher error than that generated after LSTM training.

Regarding the learning efficiency, modeling using the two algorithms driven by our dataset remains effective as long as no derivation linked to overfitting or underfitting problem has been detected by observing the loss curves.

4.2 Results in terms of performance metrics

To complete the evaluation of our machine learning model, several evaluation metrics can be used to measure its performance. The choice of metrics depends on the type of problem.

The evaluation metrics provide a quantitative assessment of a model's performance. It is recommended to use multiple metrics to get a more complete view of model performance and to tailor the metrics to the specific problem.

As we have a regression problem, the following metrics are the most suitable for judging the model performance:

- *Coefficient of determination (R-squared):*

Provides the rate of variance of the target parameter of the system. It gives an idea of whether or not the model fits the data. [41]

- *Mean squared error (MSE):*

Calculates the mean of the squares of the differences between the current values and the forecasted values. [42] We use also root MSE (*RMSE*). [43]

- *Mean absolute error (MAE):*

Calculates the average of the absolute values related to the differences between the current values and the future values. [44]

The mathematical formulas of these equations are expressed as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y})^2} \tag{11}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y})^2 \tag{12}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}| \tag{13}$$

In the case study of our dataset, the use of two algorithms was convenient as they both aim to catch

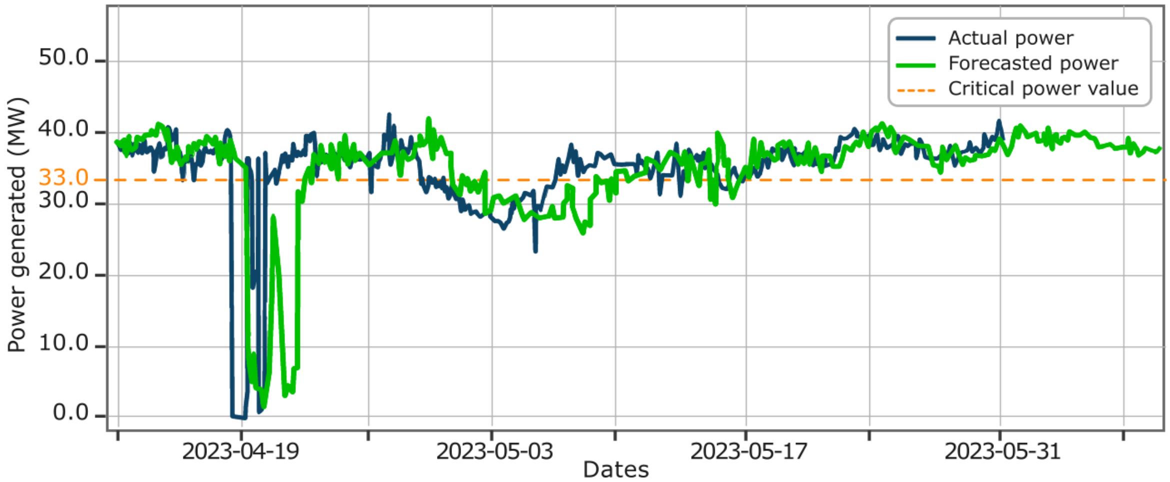

Figure. 11 Obtained curves of electrical power forecasted by the LSTM-based model

long-term reliances in sequential data.

In one side, GRU is slightly faster and requires less epochs to converge since it has a simpler architecture with fewer gates compared to LSTM.

In another side, LSTM network was softly more performant than GRU in terms of error values and performance score compared to LSTM, which will be more useful for the ability to generalize the solution on new data.

4.3 Implication of findings

At the end of the evaluation stage, we adopted the LSTM algorithm to animate our analytical model for the future prediction of the electrical power produced by the turbo-alternator group.

In Fig. 11, we presented the curve of the actual power given by the energy meter (*in blue*) superimposed on that of the power predicted by the model in Megawatts (*in green*), where we kept the same sampling period of 1 minute.

To do this task, we had set the display to show a future prediction horizon of one week ahead *(≈86,400 data points*), with a prediction history superimposed on the actual measurement of seven weeks (*≈604,800 data points*).

Using «*Matplotlib*» library [45], we plotted in Fig. 11 a horizontal line over the superposed curves (*en orange*), so that to show the critical value of the limit power. This value is equal to 33MW, and represents the nominal internal consumption of the local factory.

In fact, when the power produced is above the limit curve, it means that the Rankine thermal power plant produces more energy than the local industrial plant consumes. The excess of energy is then injected into the electrical network with which the station is connected.

On the other hand, when the real power curve is positioned below the limit curve, this means that the thermal power plant produces less than it consumes. In this case, the energy deficit is imported spontaneously from the electrical public grid, which implies its invoicing on the company, according to the criteria of duration and tariff periods fixed by the operator in charge of managing the public grid.

Therefore, the energy challenge of the company self-producing electricity is to fight against unexpected power drops. For sure, our developed model could help the companies to solve this problem of power drops, by giving the possibility to react proactively on the process parameters before that the problem occurs.

4.4 Proposal of a decision scenario and the optimal forecast horizon

By analyzing the plots of Fig. 11, we observe that there is two times where we had power drops under the critical power:

- The first was linked to a monthly scheduled and systematic shutdown of maintenance in the plant during 2 days. There was practically no significant consumption of electricity.

- The second was during the normal operating mode, and the power decreased continuously during almost 9 days, with an energy deficit varying between 1MW and 8.5MW, that gives a weighted average of 6MW (Fig. 12).

It is therefore clear that if anticipatory actions were made following the prediction model result, unwanted billing could have been avoided. This invoice was calculated at the Table 5 on the basis of the contractual tariff periods (Fig. 13) for purchasing electricity from the network of the public operator. [46]

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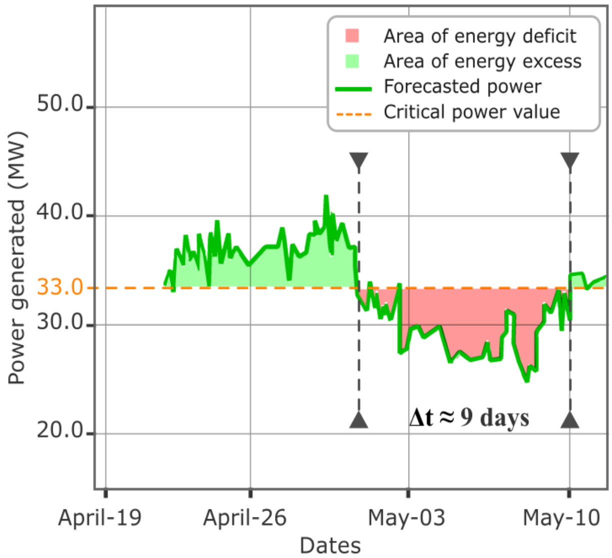

Figure. 12 Energy deficit forecasted by the model one week ahead

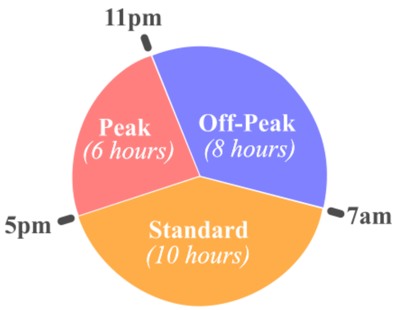

Figure. 13 number of hours considered in the dynamic pricing of energy defined in the contract of exchanging energy

Table 5. Calculation of the energy bill that could have been avoided by using the model

	Peak hours	**Standard hours**	**Off-peak hours**
Energy imported from the public grid *(MWh)*	329.4	550.2	576.8
Duration of importation *(hours)*	54.9	91.7	72.1
Cost of importation *(USD/MWh)*	97.0	85.0	70.0
Energy bill for 9 days of deficit *(USD)*	31,951.8 USD	46,767 USD	40,376 USD
	119,094.8 USD		

In addition, the model also makes it possible to give the feature vector which is likely to contribute to the power drop, which facilitates decision-making assistance, by highlighting the parameters on which action must be taken.

For this scenario, and by analyzing the variation of model features, we found that the decrease in power output has been anticipated by a gradual diminution in power factor (*parameter n°14 in the dataset of Table 3)*. The decision that the operator should have taken here is to act on the excitation of the alternator, in order to perform the synchronous compensation of the reactive energy, then ensuring the stability of the power and avoiding the unexpected bill of the Table 5.

It should be noted that the anticipatory actions should be carried out on the process parameters, and they fall into two categories:

• *Actions to perform during the running mode:*

They are generally related to the adjustment of one or more process parameters of the plant, to prevent any undesirable decrease in the output power.

• *Actions to perform during a shutdown:*

Given that for the power plant studied, one maintenance shutdown is scheduled monthly, so the best way to act is that any undesirable forecast announced by the model must be translated into actions to be planned during this shutdown opportunity.

Regarding the industrial context of this plant, the forecast horizon of one week ahead is optimal for the future prediction, as it allows to the plant managers to prepare and plan efficiently this kind of actions for the next shutdown. It helps also to define the suitable day of the monthly shutdown.

5. Conclusions and prospects

In light of the above, the added value perceived by this contribution was articulated around three key takeaways:

Firstly, before building the AI-driven prediction model for the Rankine power plant, it was essential to specify the useful variables to be extracted from the historical trends archived in the data server, through the preparation of a dataset that describes all the key operating parameters of this production cycle. Indeed, this dataset was composed of three categories of variables: the first has concerned the parameters which describe each thermodynamic transformation of this closed cycle, the second made it possible to define the system at its states of equilibrium, and the third has affected the parameters of the electrical network to which the power station is connected.

Secondly, the modeling step was done using the two deep learning algorithms GRU and LSTM, whose architecture was suitable to deal with our regression problem with supervised learning need. Subsequently, a comparative study was made between the two algorithms, which focused on the loss functions and the statistical metrics, the results obtained were excellent with a slight advantage of LSTM on the aspect of generalization of the prediction on new data.

Thridly, we were interested in the exploitation of the results produced by the model in order to help the managers of the plant in their decision-making. This help came through the generation of the electric power forecasting curve. Indeed, the prediction served to alert the users if there is some possible power drops that could come from the production side, which had allowed them to react immediately at the right time, eight 8 days before the occurrence of the problem. Finally, it was proven that this proactive action was behind the avoidance of an unwanted energy bill of 119,094.8 USD, caused by the importation of energy from the public network.

As a future prospect, there is a large scope of research on which future works could focus, among others we suggest to carry out a study following the same approach on an improved Rankine cycle, that is to say the one including the superheating stage which comes just after the steam vaporization in the boiler, this stage improves theoretically the efficiency of the cycle and optimizes energy losses in steam power plants.

Similarly, this study could be extended to renewable energies that use the same studied cycle, this direction should certainly have a laudable contribution in the field of energy transition and decarbonization of industry.

Notation list

Parameter	**Notation**
W	Mechanical work done by the system (kJ).
Q	Heat exchange of the system (kJ).
ΔU	Variation of internal energy of the system (kJ).
ΔE_k	Difference of kinetic energy (kJ).
ΔE_p	Difference of potential energy (kJ).
$\dot{w}_{ij}$	Power linked to the work during the transformation between the two equilibrium states “i” and “j” (kJ/s). We could say also that it is the rate of work done, or received by the system.
$\dot{q}_{ij}$	Power linked to the heat exchange during the transformation between the two equilibrium states “i” and “j” (kJ/s). We could say also that it is the rate of heat added to, or given by the system.
$\dot{m}_{ij}$	Mass flow rate of the fluid during the transformation between “i” and “j” (kg/s).
Δh_{ij}	Difference between specific enthalpies recorded in “i” and “j” sates (kJ/kg).
P_{gen}	Power generated by the generator of the power station (MW).
P_{int}	Power consumed by the internal factory (MW).
P_{grid}	Power exchanged between the power station and the electrical grid (MW).
y_i	Current value of the parameter y.
$\hat{y}$	Divined value of y.
$\bar{y}$	Average value of y.
N	Number of data points used.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Each author’s contribution is as follows: Conceptualization, Kossai Fakir; methodology, Kossai Fakir, Chouaib Ennawaoui and Mahmoud El Mouden; software, Kossai Fakir and Jules Alexandre Haba; validation, Chouaib Ennawaoui and Mahmoud El Mouden; formal analysis, Kossai Fakir and Jules Alexandre Haba; investigation, Chouaib Ennawaoui and Mahmoud El Mouden; resources, Kossai Fakir and Jules Alexandre Haba; data curation, Kossai Fakir and Jules Alexandre Haba; writing—original draft preparation, Kossai Fakir and Jules Alexandre Haba; writing—review and editing, Kossai Fakir, Chouaib Ennawaoui and Mahmoud El Mouden; visualization, Kossai Fakir and Jules Alexandre Haba; supervision, Chouaib Ennawaoui and Mahmoud El Mouden; project administration, Chouaib Ennawaoui and Mahmoud El Mouden; funding acquisition, Kossai Fakir.

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