Alternative Energy Sources

Renewables

Assignments

Brightspace discussion question:

“What do you think of our paper deep dives so far? Anything you like about them or would like to be different? (Be honest!)”

Due this Friday by 5pm.

Third programming assignment on identifying crops in remote sensing data (with grading rubric)

Due Friday the 3rd by midnight.

Midterm - March 9th (review on Mar 2)

Climate change in the news

Climate change in the news

A suburb in Arizona lost its source of water. Residents warn: We're only the beginning

The mega-drought is pitting neighbour against neighbour, and the repercussions are international

Alexander Panetta · CBC News · Posted: Feb 21, 2023 4:00 AM EST | Last Updated: February 21

John Hornewer pumps water from his truck into a residential tank in Rio Verde Foothills, Ariz. As the drought makes water more scarce, he's had to go farther to find it — and charge a lot more. (Jason Burles/CBC)

A man in Arizona sees a glimpse of a potentially frightening future. A future where the planet is hotter, the soil is drier, and our most precious resource is evaporating.

His job is delivering water. And his job is getting harder.

John Hornewer is now having to drive hours farther each day to fill his truck, which, in turn, fills the subterranean tanks at homes in an area outside Phoenix.

'One neighbour started peeing outside'

Ingenious and borderline-desperate water-saving tactics are being deployed.

People are now showering at nearby gyms. Some eat on paper plates. They collect rainwater in outdoor buckets and use them to flush toilets.

They flush toilets less often and promote their water-saving ways with not-entirely-tongue-in-cheek slogans like: Don't blush, share a flush.

"One neighbour started peeing outside," said one resident, Linda Vincent. "We haven't gotten to that point yet."

This county, Maricopa, is a fast-growing area in a fast-growing state.

Feuds over water: 'It's getting mean'

The competition over water allocation is pitting state versus state — Arizona versus California, primarily, have clashing views on what would be a fair allocation.

Even within states, it's pitting city-dwellers against farmers, and neighbour versus neighbour.

"It's getting mean," said local horse-breeder Mike Miola.

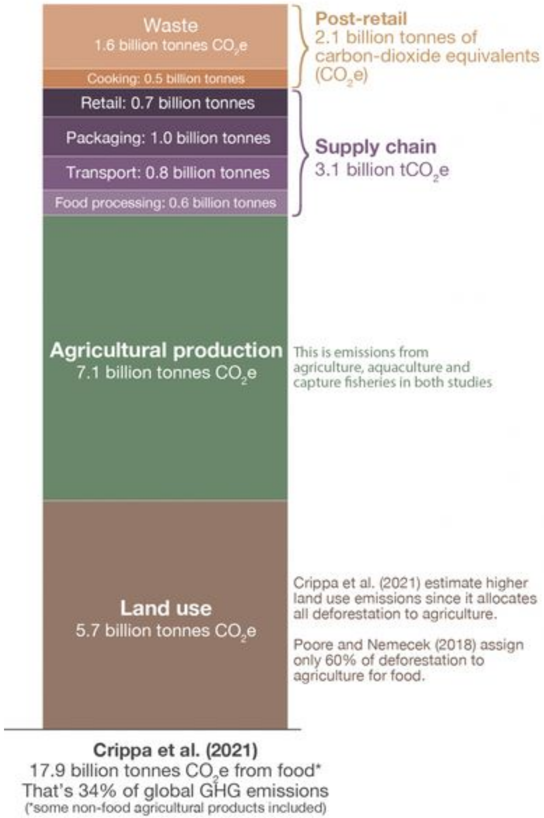
"People are angry."

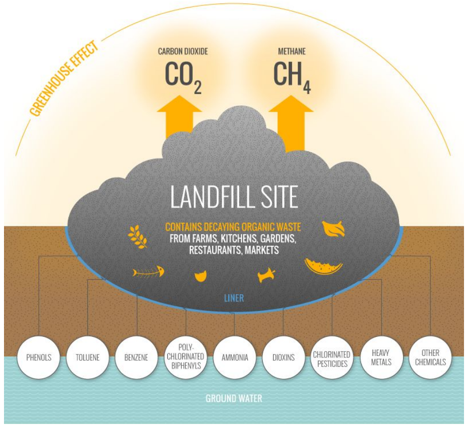
The brutal math of the Colorado River

When a treaty now involving seven states and Mexico was designed in 1922, it had been an abnormally rainy few years. The river was never going to provide the expected volumes, the 16.5 million acre-feet (about 20 billion cubic metres) allocated per year.

Then came the population explosion. Metropolises like Las Vegas, Los Angeles, San Diego and Phoenix sprouted in what was originally a farming region, blowing past the 16.5-million-acre-foot target.

Recap





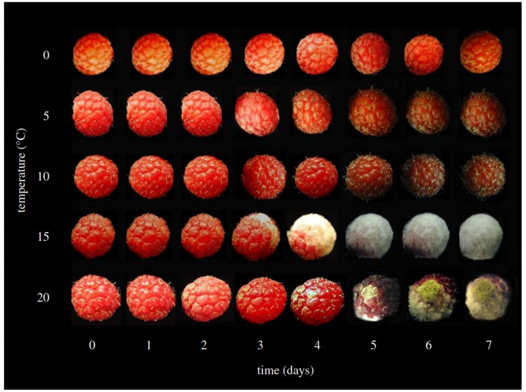
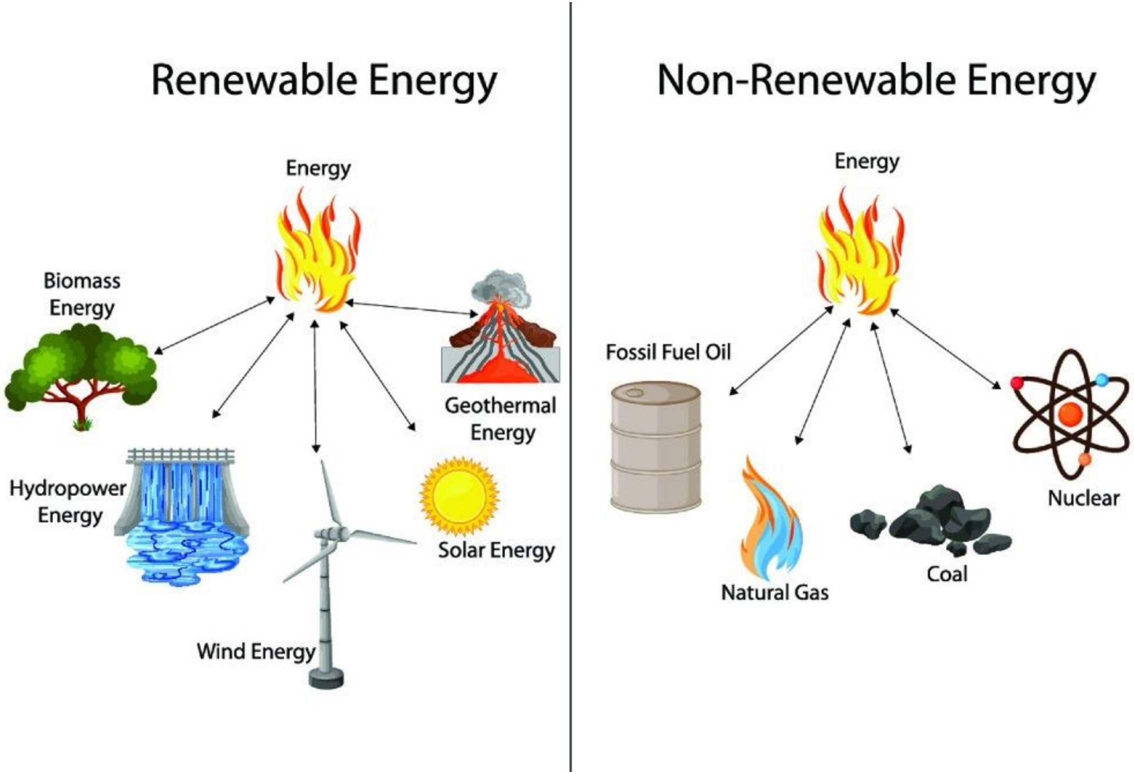
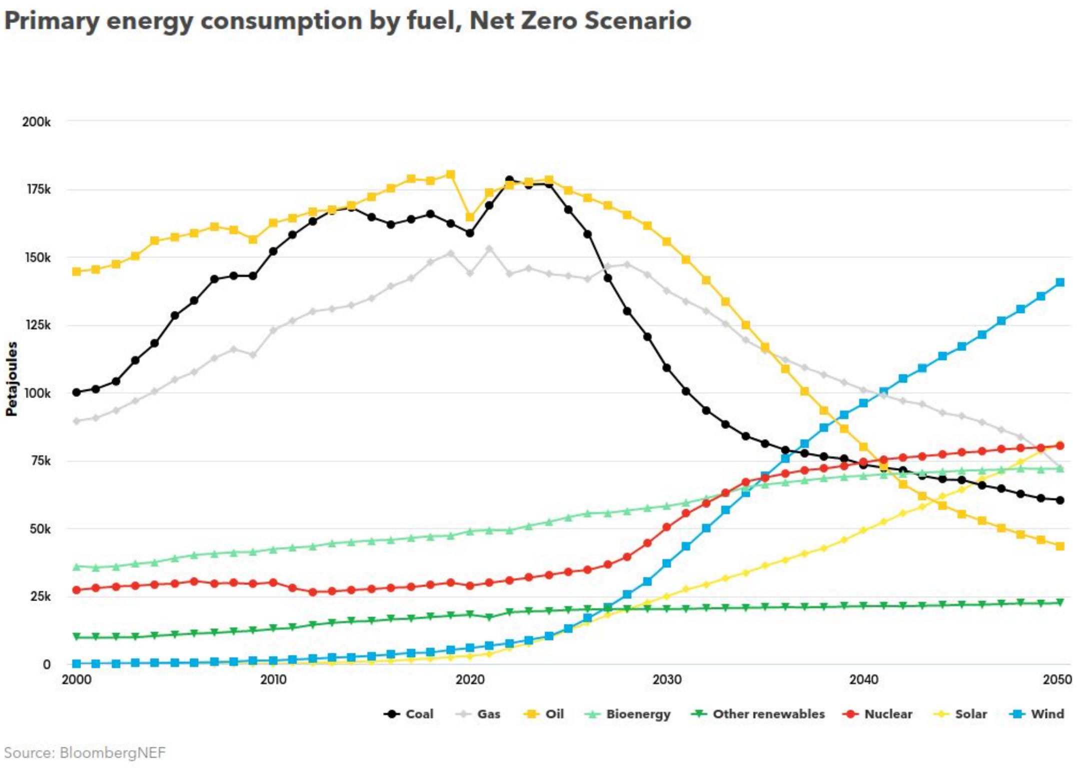


Figure 8. Impact of temperature on the appearance of 'Killarney' red raspberries during a storage period of 7 days [4,6]. (Online version in colour.)

Energy Sources



The need to produce more energy from clean sources



The need to produce more energy from clean sources

Global AI in Energy Market to Reach $7.78 Billion by 2024

BIS Research
Emerging Technology Market Intelligence

NEWS PROVIDED BY
BIS Research →
Jan 09, 2020, 08:30 ET

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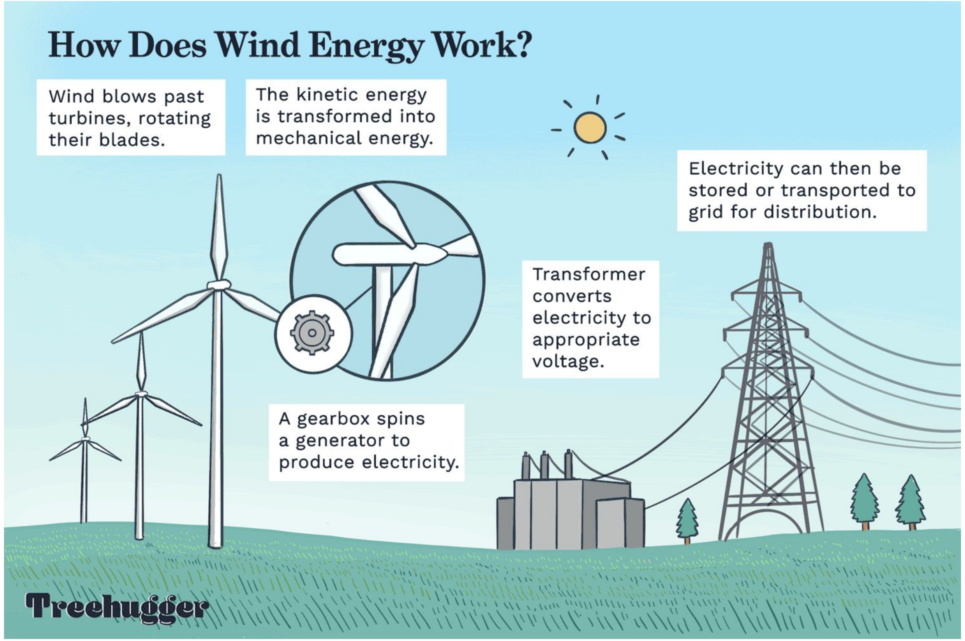
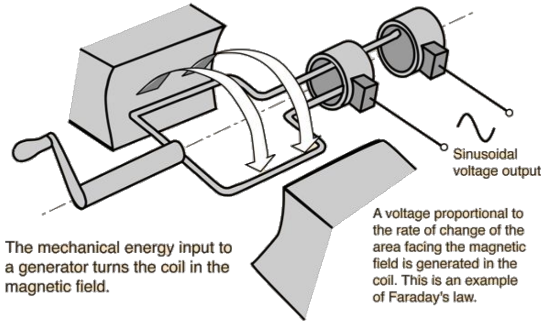
FREMONT, California, Jan. 9, 2020 /PRNewswire/ -- According to a new market intelligence report by BIS Research titled **'Global Artificial Intelligence (AI) in Energy Market - Analysis and Forecast, 2019-2024'**, the artificial intelligence in energy market is expected to reach $7.78 billion by 2024. The market is projected to witness a CAGR of 22.49% from 2019 to 2024. This growth is anticipated to be driven by the demand for increasing operational efficiency, rising concern for energy efficiency, growing market penetration of decentralized power generation, and rising concern for battery storage systems.

Wind turbines

Convert kinetic energy of air into electric power using a generator.





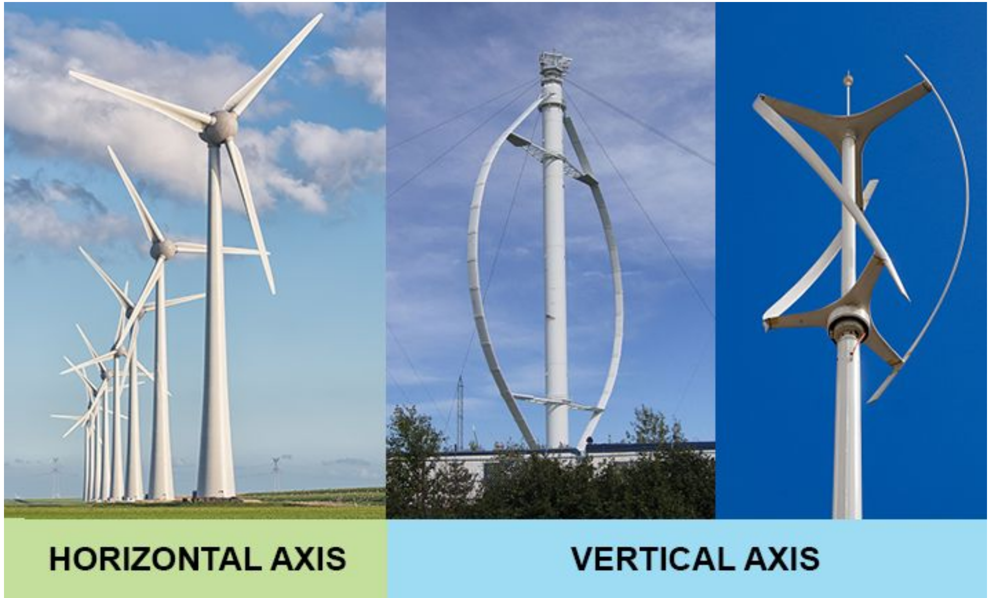
http://hyperphysics.phy-astr.gsu.edu

Wind turbines

Convert kinetic energy of air into electric power using a generator.

Can be horizontal or vertical.

Horizontal are more common and can produce more energy, but come with high costs of sound pollution, space needs, wildlife interference, and failure due to environmental damage.



Wind turbines

Focused on maintenance: monitor functions and detect scenarios that might trigger maintenance, e.g., detect significant deviations from normal operation in the turbine.

Article

Machine Learning for Wind Turbine Blades Maintenance Management

Alfredo Arcos Jiménez [1], Carlos Quiterio Gómez Muñoz [2] and Fausto Pedro García Márquez [1,*]

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2 Ingeniería Industrial y Aeroespacial, Universidad Europea Madrid, Villaviciosa de Odón, 28670 Madrid, Spain; carlosquiterio.gomez@universidadeuropea.es
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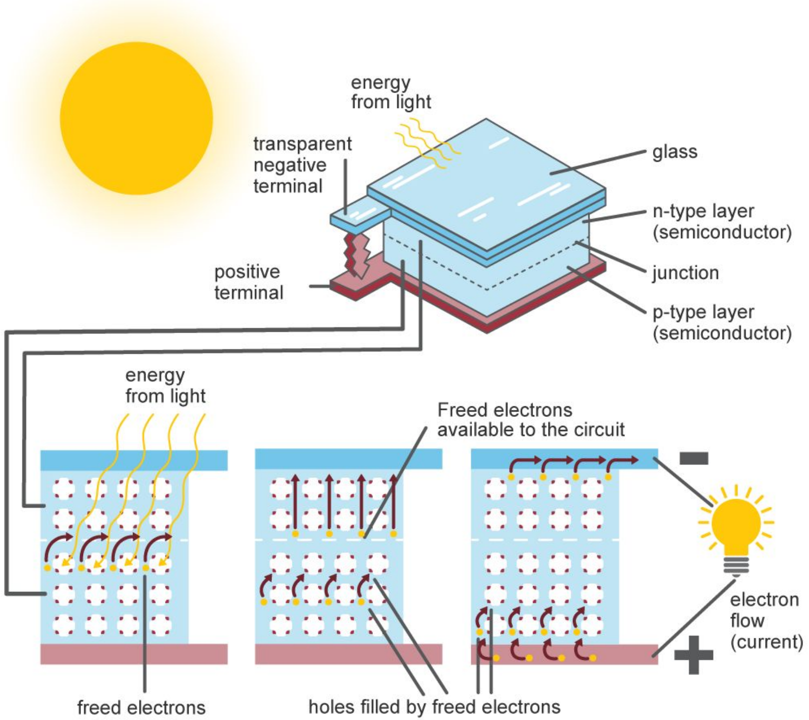
Received: 28 October 2017; Accepted: 18 December 2017; Published: 21 December 2017

Abstract: Delamination in Wind Turbine Blades (WTB) is a common structural problem that can generate large costs. Delamination is the separation of layers of a composite material, which produces points of stress concentration. These points suffer greater traction and compression forces in working conditions, and they can trigger cracks, and partial or total breakage of the blade. Early detection of delamination is crucial for the prevention of breakages and downtime. The main novelty presented in this paper has been to apply an approach for detecting and diagnosing the delamination WTB. The approach is based on signal processing of guided waves, and multiclass pattern recognition using machine learning. Delamination was induced in the WTB to check the accuracy of the approach. The signal is denoised by wavelet transform. The autoregressive Yule–Walker model is employed for feature extraction, and Akaike's information criterion method for feature selection. The classifiers are quadratic discriminant analysis, k-nearest neighbors, decision trees, and neural network multilayer perceptron. The confusion matrix is employed to evaluate the classification, especially the receiver operating characteristic analysis by: recall, specificity, precision, and *F*-score.

Photovoltaic solar panels

A photovoltaic cell is composed of many layers of materials, each with a specific purpose. The most important layer of a photovoltaic cell is the specially treated semiconductor layer. It is composed of two distinct layers (**p-type and n-type**), and is what actually converts the Sun's energy into useful electricity through a process called the photovoltaic effect . On either side of the semiconductor is a layer of conducting material which "collects" the electricity produced

Inside a photovoltaic cell



Source: U.S. Energy Information Administration

https://energyeducation.ca/encyclopedia/Photovoltaic_cell

Photovoltaic solar panels

ML algorithms are used to enhance current structural designs and materials of photovoltaic cells and solar thermal systems.

Contents lists available at ScienceDirect

Solar Energy Materials and Solar Cells

journal homepage: http://www.elsevier.com/locate/solmat

ELSEVIER

Machine learning analysis on stability of perovskite solar cells

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ARTICLE INFO

Keywords:
Perovskite solar cells
Data mining
Machine learning
Association rule mining
Stability
Knowledge extraction

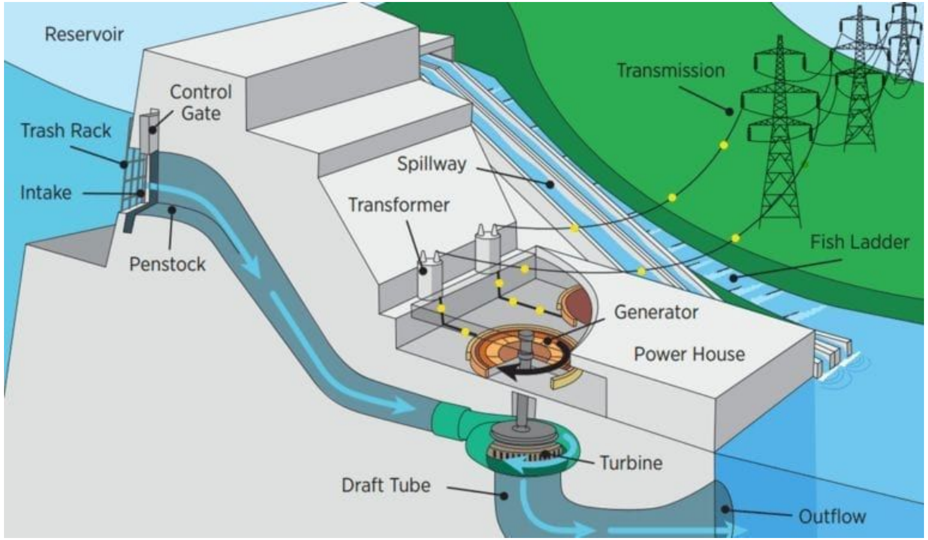
ABSTRACT

In this work, a dataset containing long-term stability data for 404 organolead halide perovskite cells was constructed from 181 published papers and analyzed using machine-learning tools of association rule mining and decision trees; the effects of cell manufacturing materials, deposition methods and storage conditions on cell stability were investigated. For regular cells, mixed cation perovskites, multi-spin coating as one-step deposition, DMF + DMSO as precursor solution and chlorobenzene as anti-solvent were found to have positive effects on stability; SnO_2 as ETL compact layer, PCBM as second ETL, inorganic HTLs or HTL-free cells, LiTFSI + TBP + FK209 and F4TCNQ as HTL additives and carbon as back contact were also found to improve stability. The cells stored under low humidity were found to be more stable as expected. The degradation was slightly faster in inverted cells under humid condition; the use of some materials (like mixed cation perovskites, PTAA and NiO_x as HTL, PCBM + C60 as ETL, and BCP interlayer) were found to result in more stable cells.

Hydropower

Hydropower plants are one of the oldest mechanisms used to produce power due to their simplistic mechanisms.

Very efficient: reaching up to 95% efficiency for large scale and 85% in small scale applications.



Hydropower

Machine learning mainly has applications to basic operations and fault detection

Contents lists available at ScienceDirect

Computers in Industry

journal homepage: www.elsevier.com/locate/compind

ELSEVIER

Condition monitoring and fault diagnostics for hydropower plants

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Keywords:
Industrial product-service systems
Condition monitoring
Fault diagnostics
Support vector machines

ABSTRACT

This paper presents a condition monitoring and fault diagnostics (CMFD) system for hydropower plants (HPP). CMFD is based on the concept of industrial product-service systems (IPS2), in which the customer, turbine supplier, and maintenance service provider are the IPS2 stakeholders. The proposed CMFD consists of signal acquisition, data transfer to the virtual diagnostics center (VDC) and fault diagnostics. A support vector machine (SVM) classifier has been used for fault diagnostics. CMFD has been implemented on an HPP with three Kaplan units. A signal acquisition system for CMFD consists of data acquisition from a unit control system and a supplementary system for high-frequency data acquisition. The implemented SVM method exhibits high training accuracy and thus enables adequate fault diagnostics. The data are analyzed in the VDC, which allows all stakeholders access to diagnostic information from anywhere at any time. Based on this information, the service providers can establish condition-based maintenance and offer operational support. Furthermore, through the VDC, cooperation between the stakeholders can be achieved; thus, better maintenance scheduling is possible, which will be reflected in higher system availability.

Weather prediction

Wind, solar, and hydropower systems all benefit from more accurate prediction of climate factors

Evolutionary artificial neural networks for accurate solar radiation prediction

D. Guijo-Rubio [a, *, 1], A.M. Durán-Rosal [b, 1], P.A. Gutiérrez [a], A.M. Gómez-Orellana [a], C. Casanova-Mateo [c, d], J. Sanz-Justo [c], S. Salcedo-Sanz [e], C. Hervás-Martínez [a]

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A data-driven multi-model methodology with deep feature selection for short-term wind forecasting

Cong Feng [a], Mingjian Cui [a], Bri-Mathias Hodge [b], Jie Zhang [a,*]

[a] *Department of Mechanical Engineering, University of Texas at Dallas, Richardson, TX 75080, USA*
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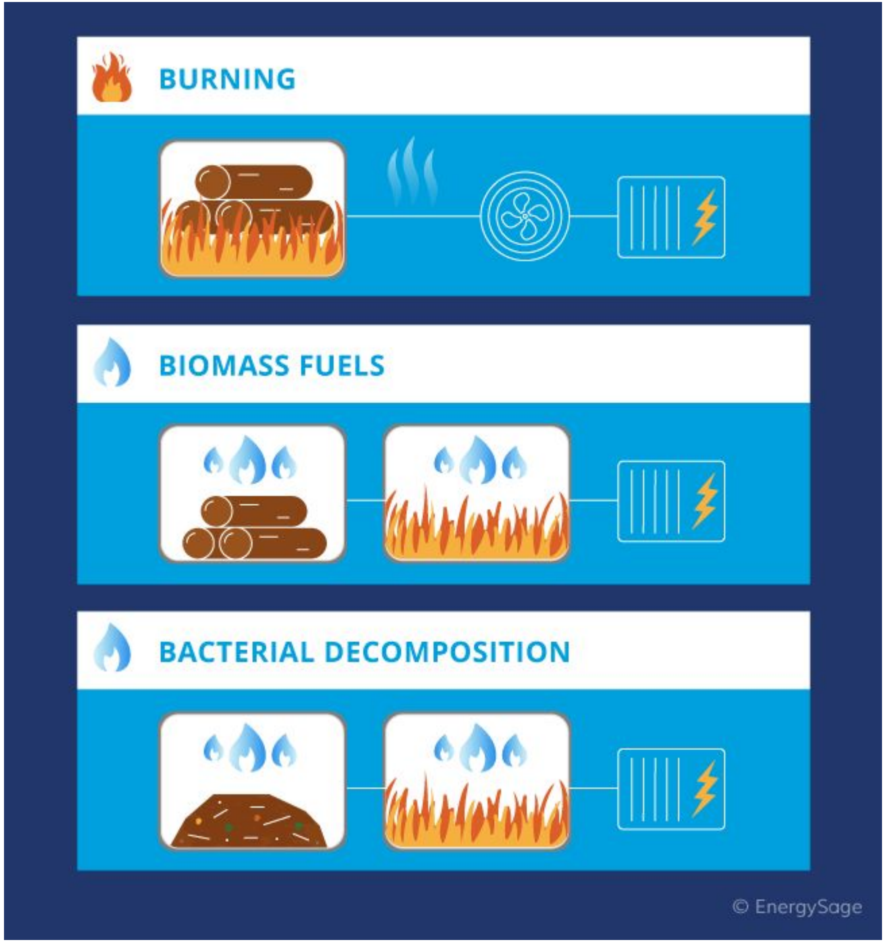
Article

Smart Climate Hydropower Tool: A Machine-Learning Seasonal Forecasting Climate Service to Support Cost–Benefit Analysis of Reservoir Management

Arthur H. Essenfelder [1,2,*], Francesca Larosa [1,2], Paolo Mazzoli [3], Stefano Bagli [3], Davide Broccoli [3], Valerio Luzzi [3], Jaroslav Mysiak [1,2], Paola Mercogliano [2] and Francesco dalla Valle [4]

Bioenergy

Biomass is converted into energy through different methods: Solid biomass can be burned to produce steam at high pressure to move a turbine and a generator. Through a gasifier, biomass can be converted into syngas, a synthesis gas that mainly consist of hydrogen, methane, carbon monoxide, and carbon dioxide. Additionally, biomass could be chemically converted into pyrolysis oil using heat, thus making it suitable for transportation.



Bioenergy

Machine learning can be used to bypass computationally expensive calculations of, e.g., the gasification process.

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

ELSEVIER

Predictive modeling of biomass gasification with machine learning-based regression methods

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A R T I C L E I N F O

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Machine learning
Decision tree regression
Multilayer perceptron
Support vector regression

A B S T R A C T

Biomass gasification is a promising power generation process due to its ability to utilize waste materials and similar renewable energy sources. Predicting the outcomes of this process is a critical step to efficiently obtain the optimal amount of products. For this purpose, various kinetic and equilibrium models are proposed, but the assumptions made in these models significantly reduced their practical usability and consistency. More recently, machine learning methods have started been employed, but the limited selection of methods and lack of implementation of cross-validation techniques caused insufficiency to obtain unbiased performance evaluations. In this study, we employed four regression techniques, i.e., polynomial regression, support vector regression, decision tree regression and multilayer perceptron to predict CO, CO_2, CH_4, H_2 and HHV outputs of the biomass gasification process. The data set is experimentally collected via downdraft fixed-bed gasifier. PCA technique is applied to the extracted features to prevent multicollinearity and to increase computational efficiency. Performances of the proposed regression methods are evaluated with k-fold cross validation. Multilayer perceptron and decision tree regression performed the best among other methods by achieving $R^2 > 0.9$ for the majority of outputs and were able to outperform other modeling approaches.

Paper Deep Dive

ELSEVIER

Applied Energy
Volume 200, 15 August 2017, Pages 155-169

Image-based deep neural network prediction of the heat output of a step-grate biomass boiler

Pál Tóth [a b], Attila Garami [a], Bernadett Csordás [a]

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https://doi.org/10.1016/j.apenergy.2017.05.080

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Highlights

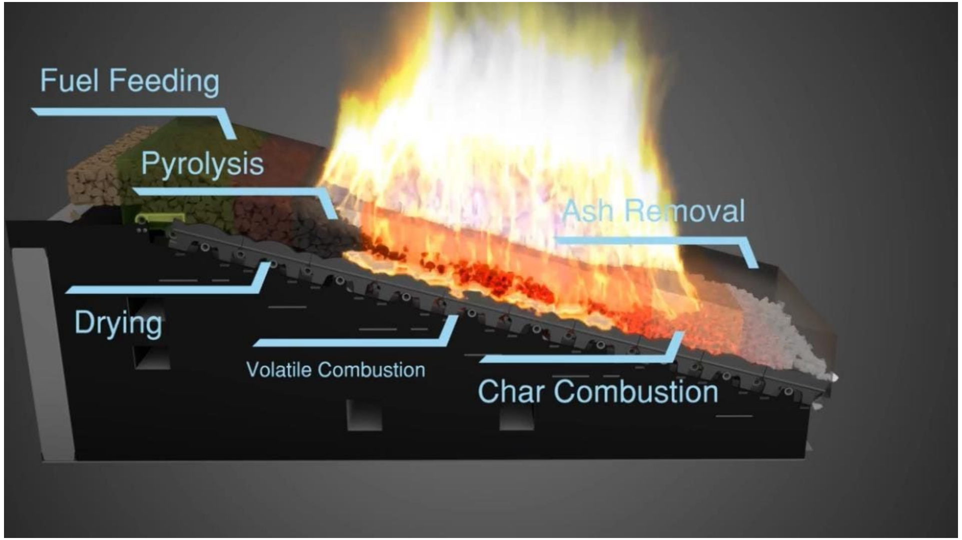
- A deep learning-based system was developed for the monitoring of biomass combustion.
- The system can predict the heat output of a step-grate boiler up to 30min ahead.
- The water temperature predictions are accurate up to $\pm 1\,^{\circ}$C.
- The system has great potential in optimizing step-grate biomass combustion.

https://www.sciencedirect.com/science/article/pii/S0306261917305822

Optimizing grate fired biomass boilers

"Grate firing is the most widely used method for biomass combustion.

Grate-fired boilers are known to have lower efficiency compared to e.g., fluidized bed combustors, therefore, given the share of the technology in global renewable energy production, it is important to optimize their operation."



Direct goal: predict output water temperature ***in real time***

“The motivation behind the prediction system is the desire to eliminate or reduce uncertainty caused by heterogeneous fuel quality and highly complex combustion process in systems operated under varying loads. Such a prediction system is meaningful in boiler systems that operate without installed on-line fuel analysis systems (e.g., on-line moisture analyzers).”

“The objective of the prediction system was to predict the output water temperature of the boiler in a multistep-ahead scheme in order to help issue warnings regarding potential future operating problems and facilitate robust control.”

Brainstorm

What kind of data would you want to have to be able to approach this problem?

What kind of methods would you apply?

How would you measure success?

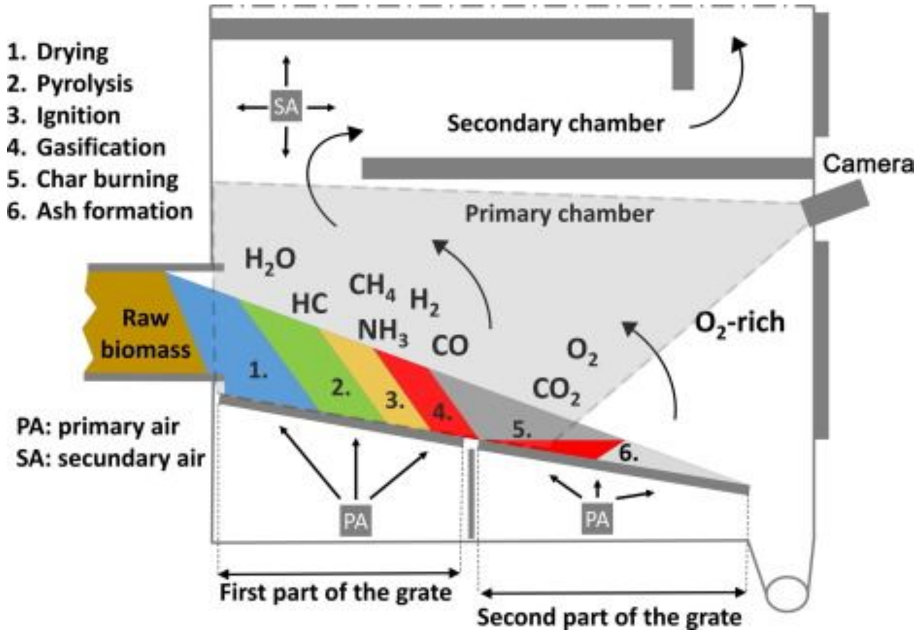
What difficulties might you face?

Innovation: Use images to predict

“It is hypothesized that flame images contain quasi-instantaneous information about the combustion process and fuel properties. If this hypothesis is valid, flame imaging can become an inexpensive and reliable tool for the optimization of boiler operation, offering additional benefits, i.e., from the point of process safety.”

Data Collection

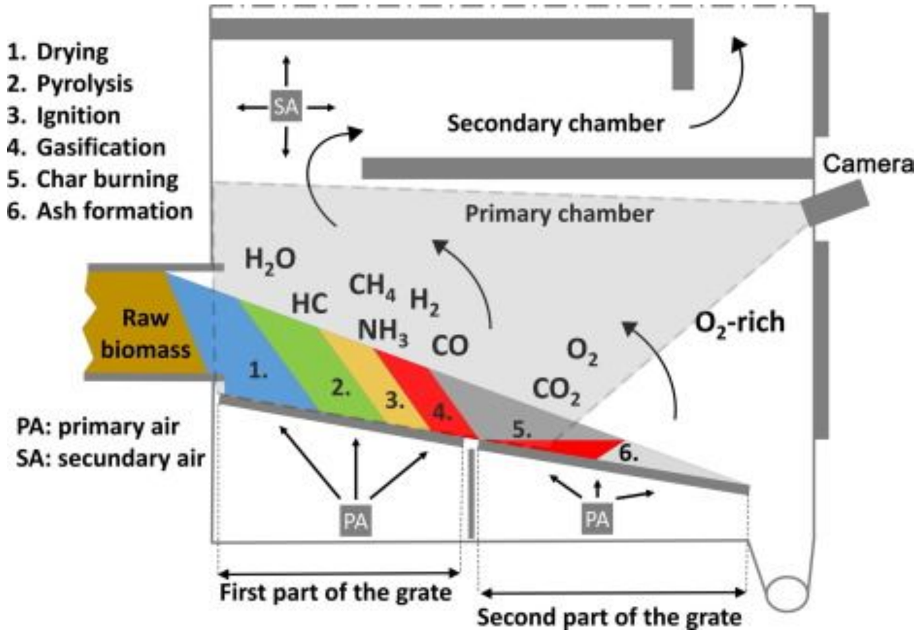
The boiler was equipped with an on-line measurement system integrated into a distributed control system (DCS) that monitored several operational parameters, including **chamber temperature, return and output water temperatures, fan speeds, boiler capacity** and hydraulic pressures of the step-grate, fuel feeding and de-ashing systems. An additional electrochemical cell flue gas analyzer was installed to record CO2 emissions



The boiler was integrated into a sawmill process, producing heat for steaming timber products. Wood chips, by-products of the sawing process were used as fuel. PA and SA are air sources.

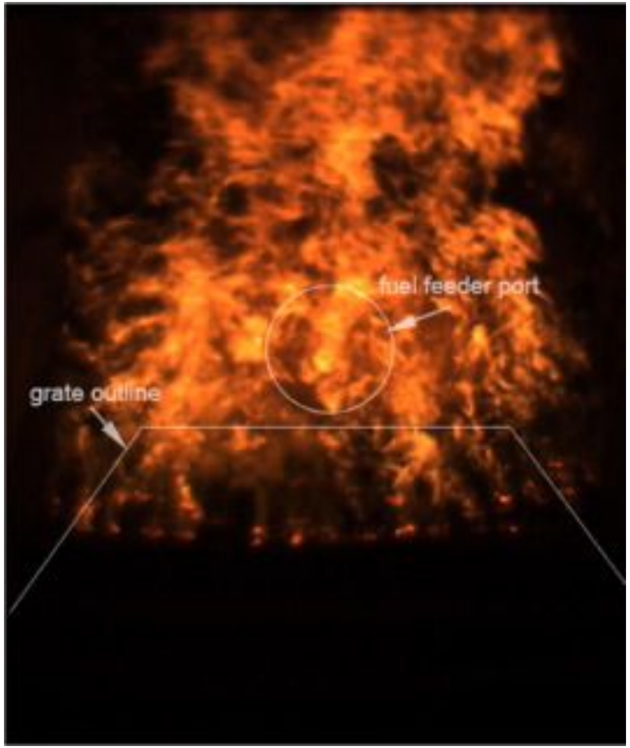
Data Collection

The lens and the camera were protected by a tube-in-a-tube type cooling system. Compressed air was used as a coolant. Small holes in the front-end piece of the stainless steel housing, outside of the first optical element in the lens, ensured positive pressures inside the pinhole lens, therefore avoiding dust deposition. The cooling system of the camera maintained lens and camera temperatures below 30 °C.



Data Collection

Flame images were acquired by using a Basler Ace acA1300-22gc model digital camera. The camera utilized a global shutter CCD sensor. Images were acquired at a rate of 13 Hz. The exposure time of the sensor was set at 0.75 ms—this made sure that little to no pixel saturation and image streaking occured in the images. The pixel resolution of the images was 488 × 582. Images were RGB.



Computation problem!

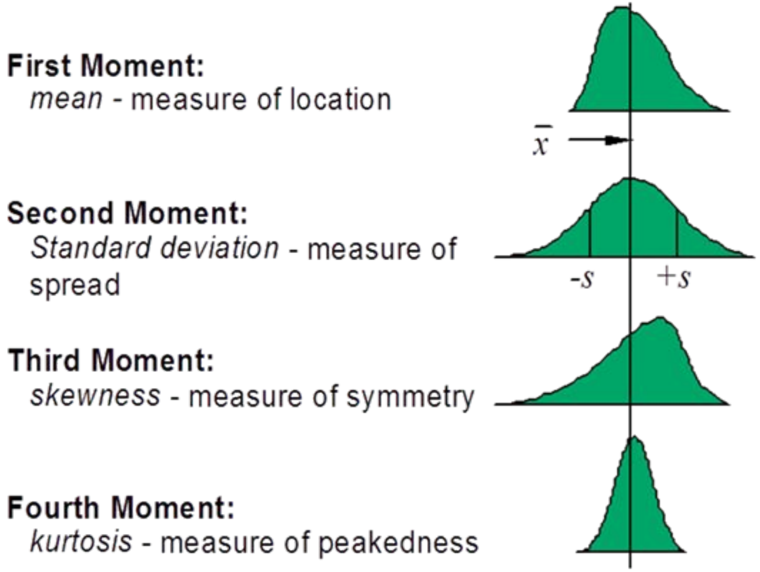
“Since the images had a pixel resolution of 488 × 582 with an RGB bit depth of 24 bit, and the camera operated at 13 Hz, the image data rate was approximately 11 million 8-bit integers per second.”

Too much for ***real time*** computing. What can be done?

Solution: Subsampling

Many options for subsampling but here they:

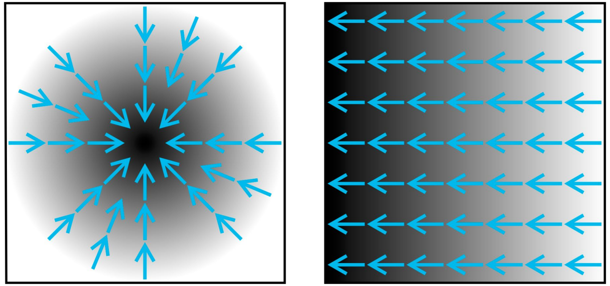
1. Calculate the first four statistical moments (the mean, variance, skewness and kurtosis) of each color channel

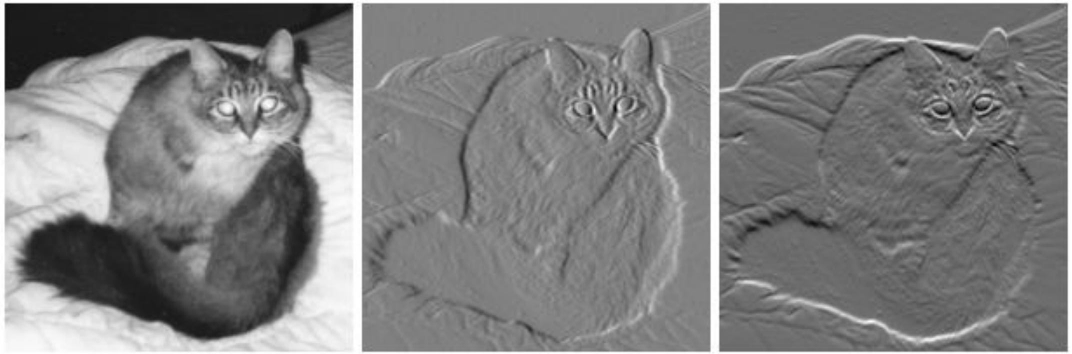


Solution: Subsampling

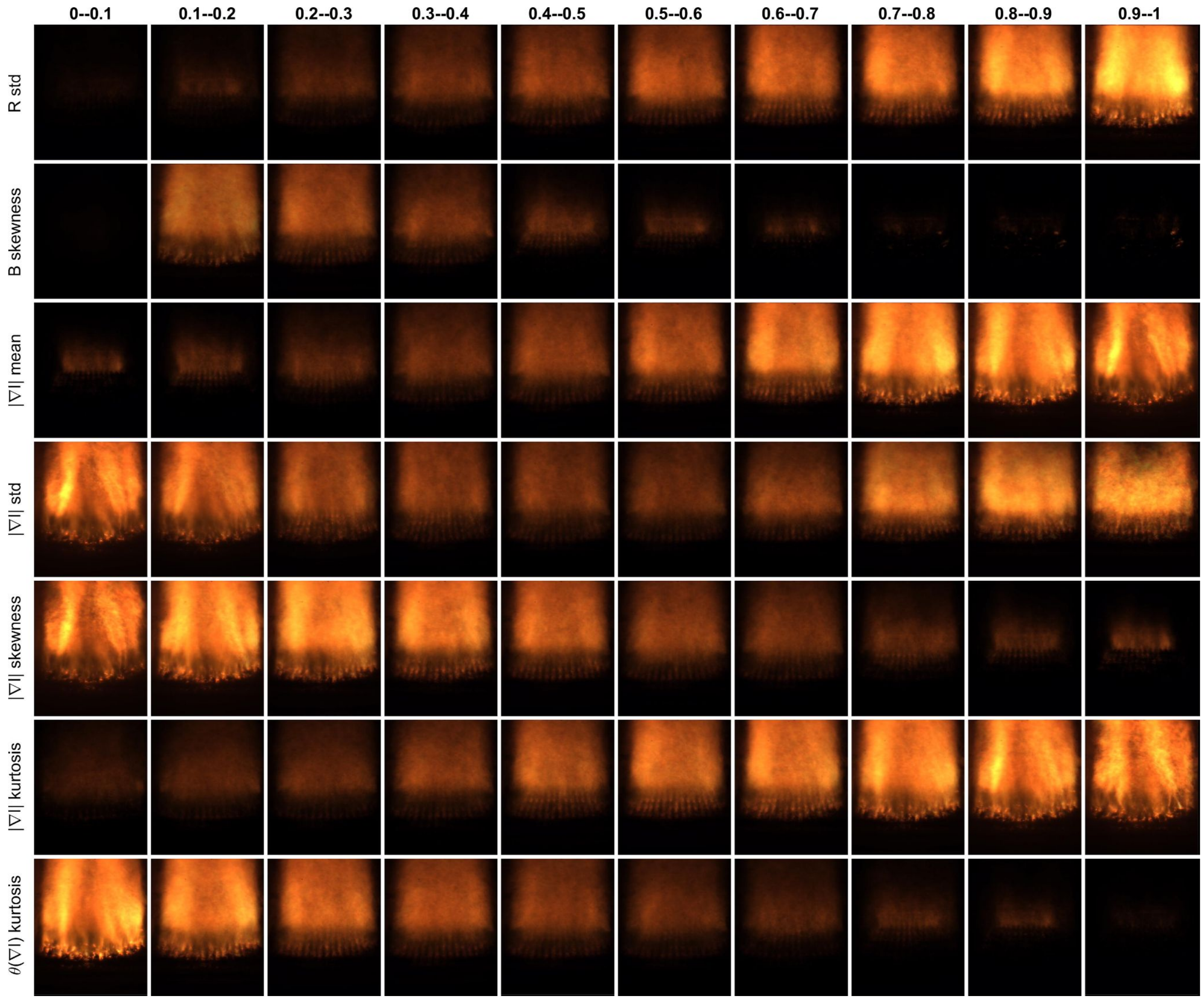
Many options for subsampling but here they:

1. Calculate the first four statistical moments (the mean, variance, skewness and kurtosis) of each color channel
2. Take the spatial gradient of the red channel and calculate the first four moments of its magnitude and orientation.





Averaged images for different feature values.



Solution: Subsampling

> “The more elegant and exact methods for data reduction (e.g., PCA) were not used in the current study, because lower statistical moments (the mean and variance) can be intuitively interpreted by human operators. As part of a monitoring system for an industrial process overseen by humans, the benefit of being human-readable outweighed the potential benefits of optimal data representation.”

Non-image input features

“Seven of the many recorded parameters were selected as inputs for the machine learning system: **boiler capacity percentage, output water temperature, return water temperature, flue gas O2 content and the capacities of primary and secondary air fans.** It is important to note here that the predicted quantity is the future values of the output water temperature, but its current (instantaneous) value is used as an input feature as well. In other words, when computing predictions at very short times ahead, the predictions should be dominantly determined by the current value of the output water temperature.”

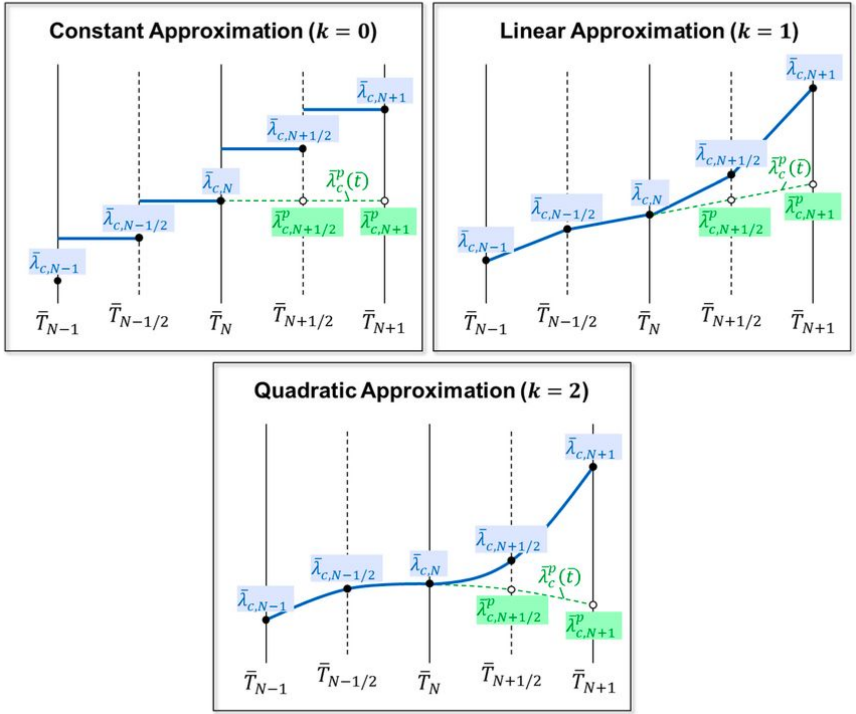
Data problem!

“Another important point is the temporal synchronization of the measurements from the DCS with image data. Since the camera operated at 13 Hz, a set of image features was available at approximately every 80 ms, while the DCS collected measurements much less frequently, once in every 10 s (the low sampling frequency was necessary due to strict long-term archiving requirements). ”

What can be done?

Solution: constant interpolation

“The coarser data, entries from the DCS, were synchronized with image data by using a piecewise constant extrapolation scheme—the values of the operating parameters were kept the same as those of the last available entry in the coarser dataset, until a set of updated values became available.”



Example data

The boiler has intrinsic cycles reflected in the data.

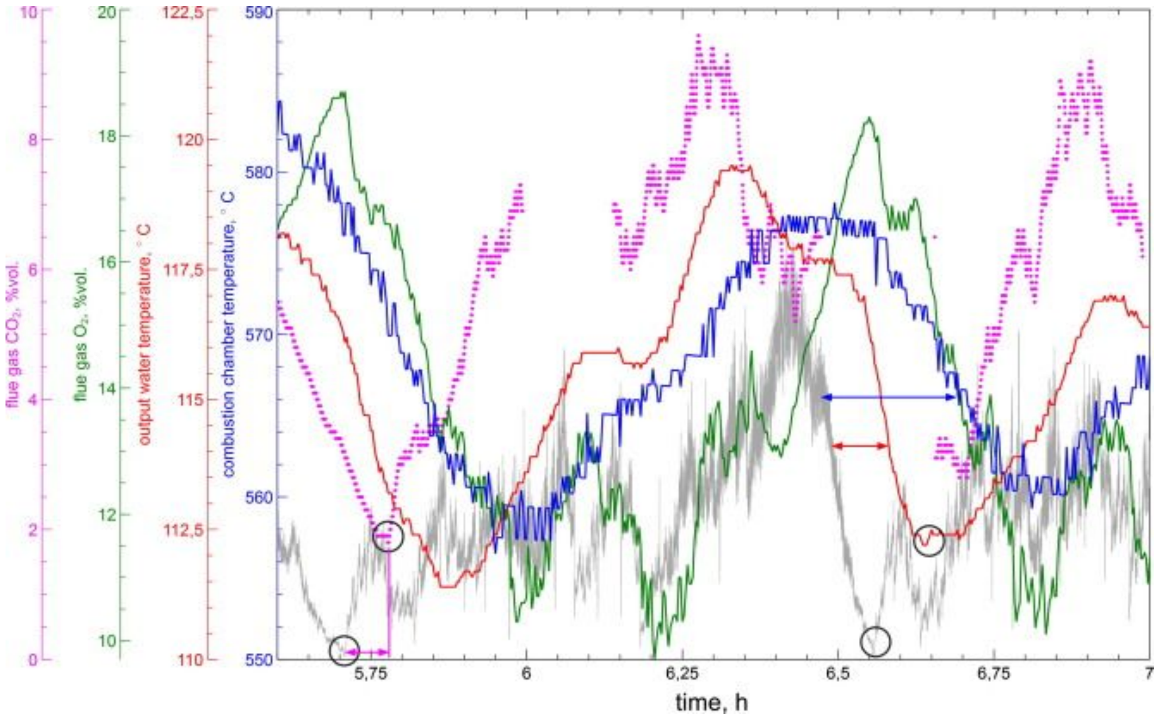
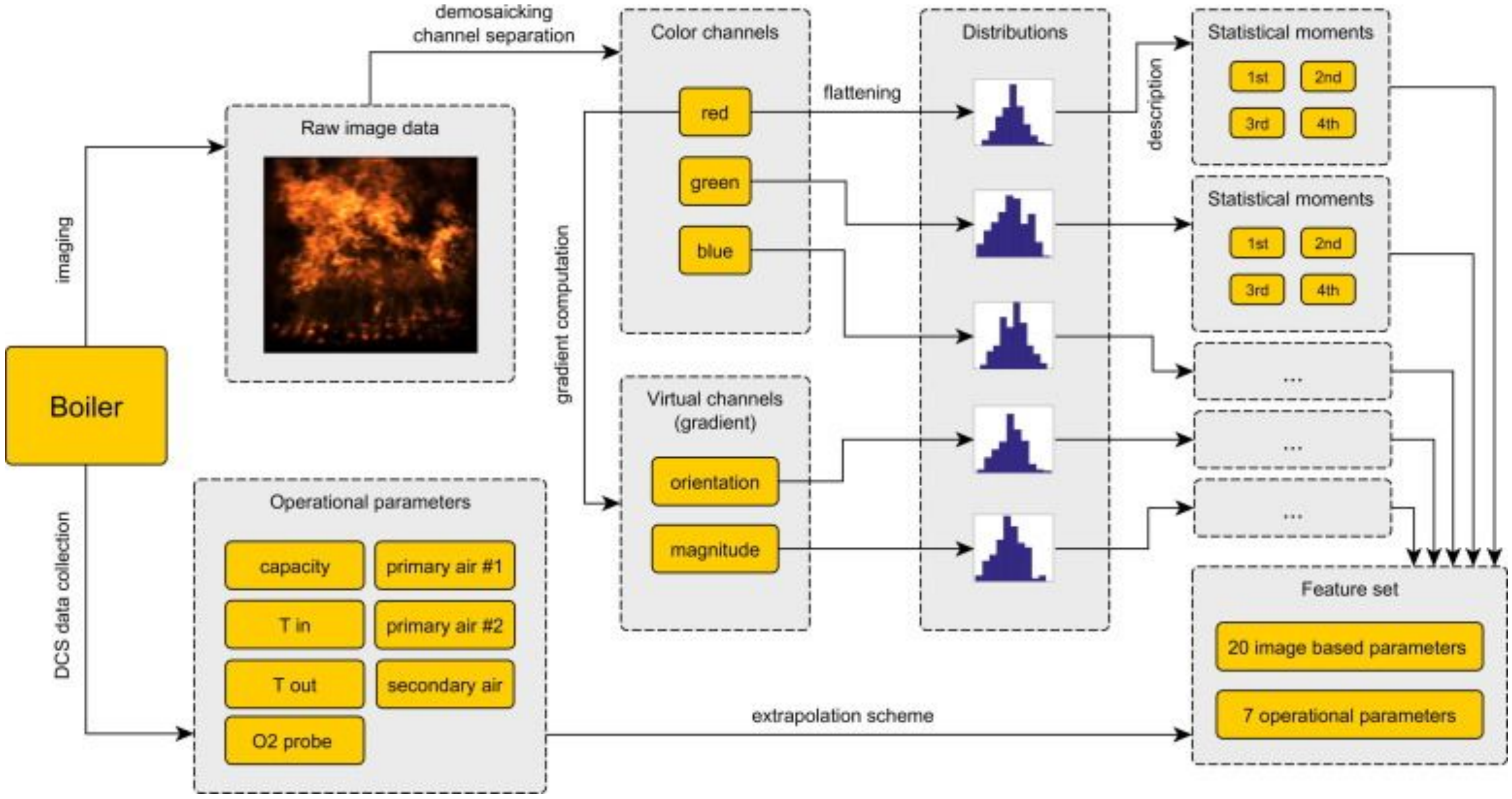


Fig. 6. The mean intensity of the red channel (gray line), combustion chamber temperature (blue line), output water temperature (red line), flue gas O_2-content (green line) and flue gas CO_2-content (magenta dots) as a function of time. Circles denote the "down" phases of the boiler cycles as they appear in different time series. Arrows denote the time lag between the imaging measurement and other measurements—arrow colors indicate the corresponding conventional sensor signal. As seen, all conventional measurements lag behind the image signal, with CO_2 and O_2 showing the quickest, and combustion chamber temperature showing the slowest response. Missing data in the CO_2 signal are caused by the automatic recalibration of the flue gas analyzer. (For

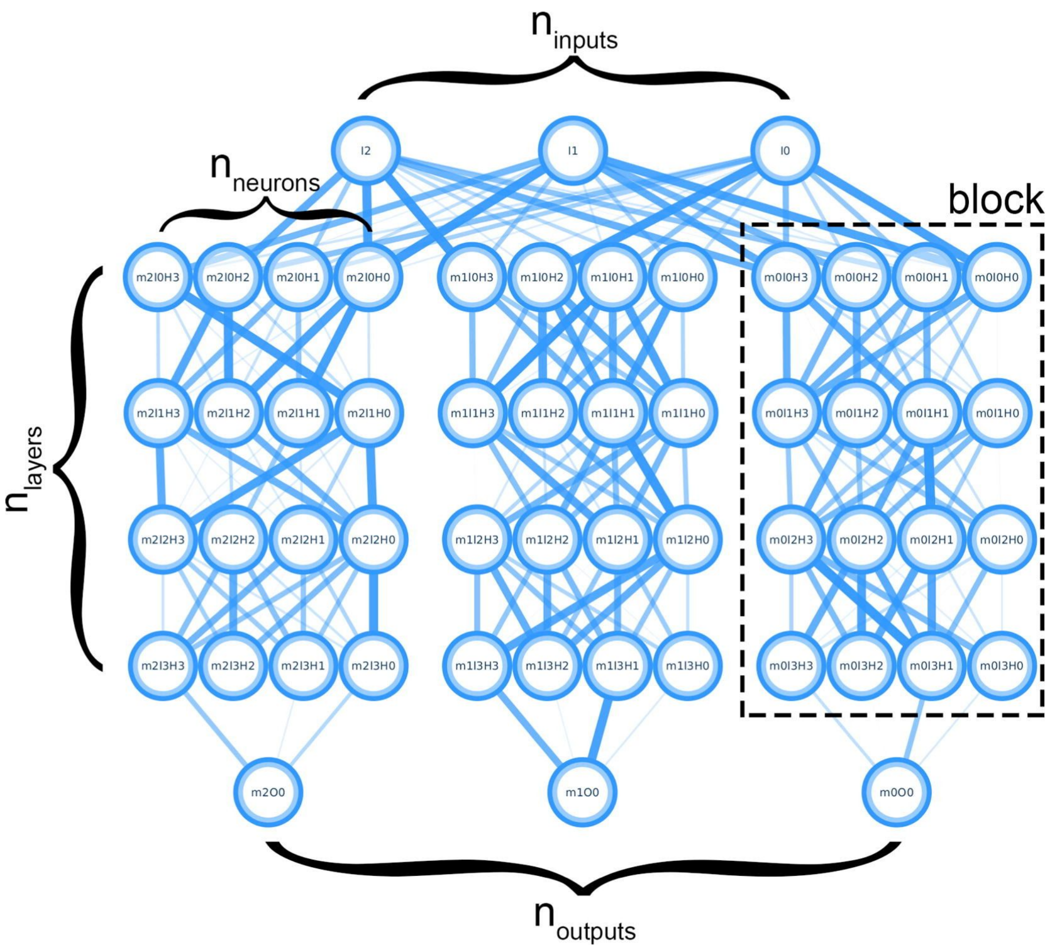
Feature Summary



Model

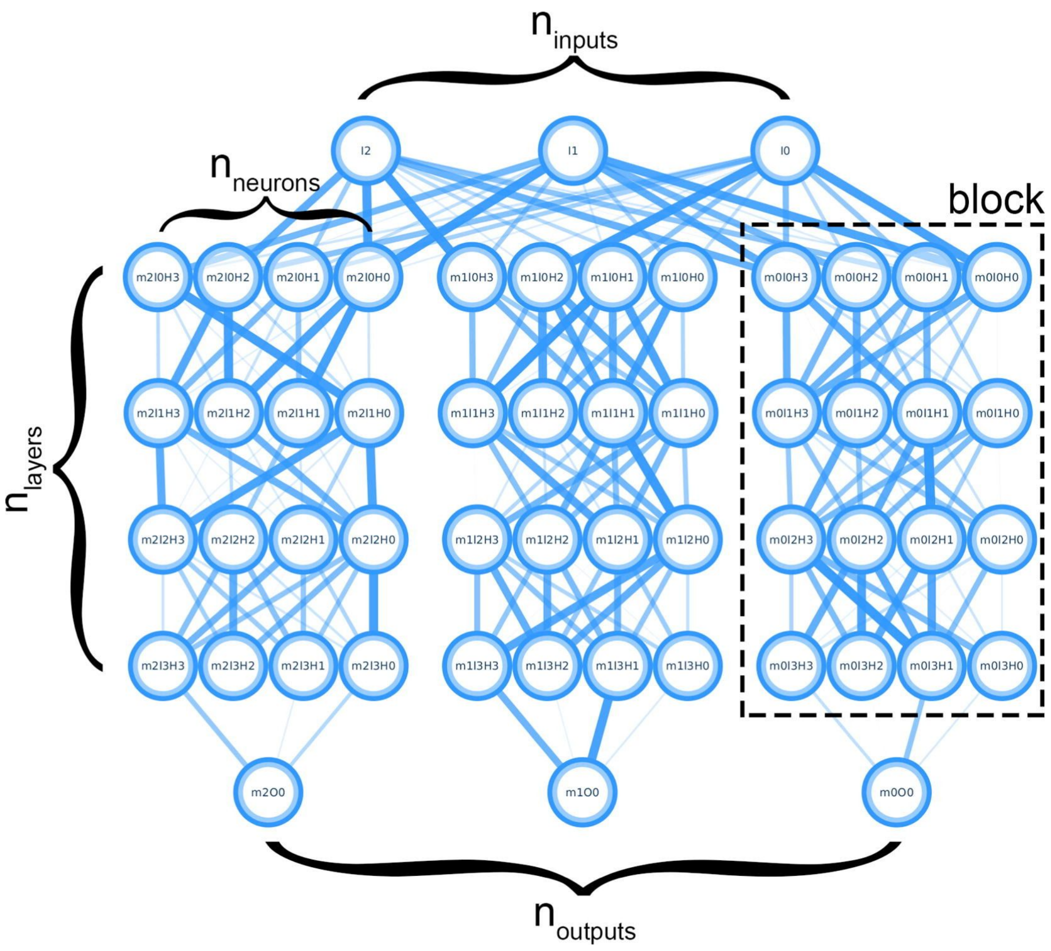
Time steps were spaced 8 seconds apart, up to (8 seconds x 200 =) 28 minutes ahead.

This creates multiple predictions for the same time bin, therefore producing a distribution.



Model

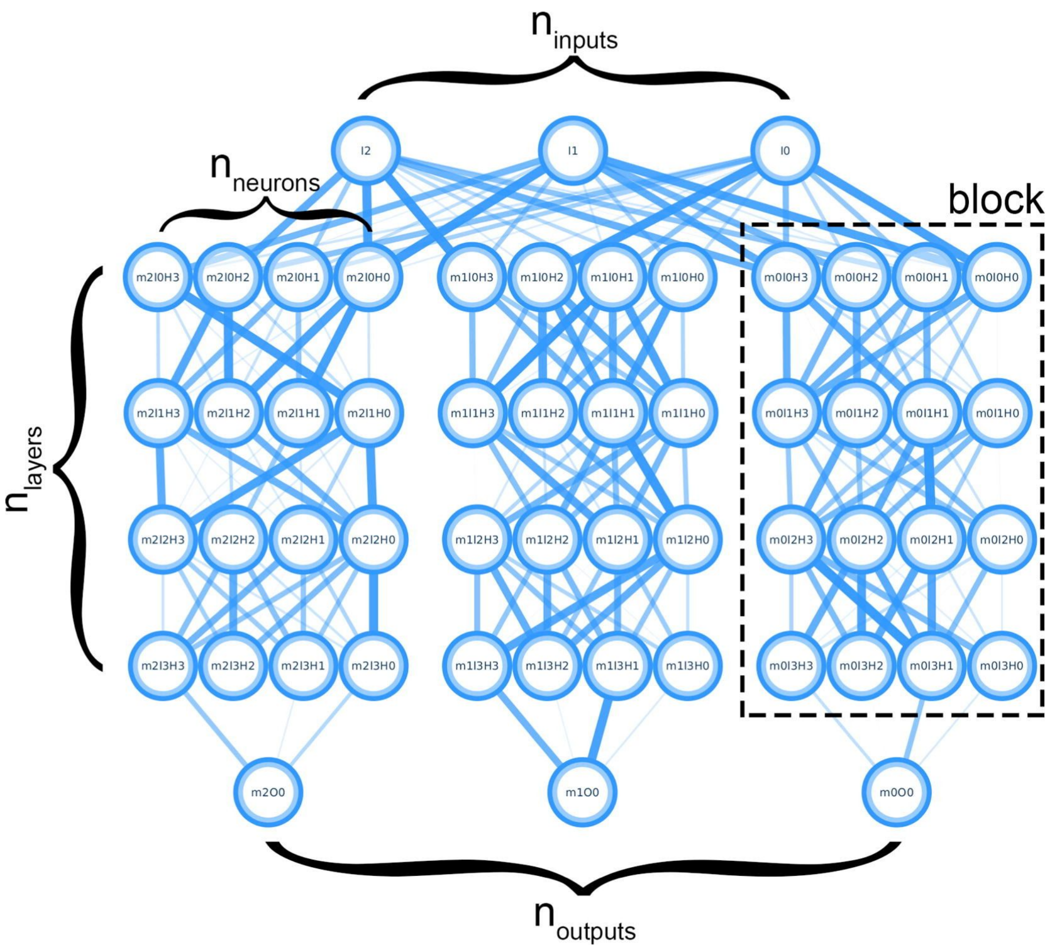
Neural network(s) with 27 input features and (200) different hidden unit blocks and outputs for different future time steps. Each block has 5 hidden layers with 50 neurons each.



Model

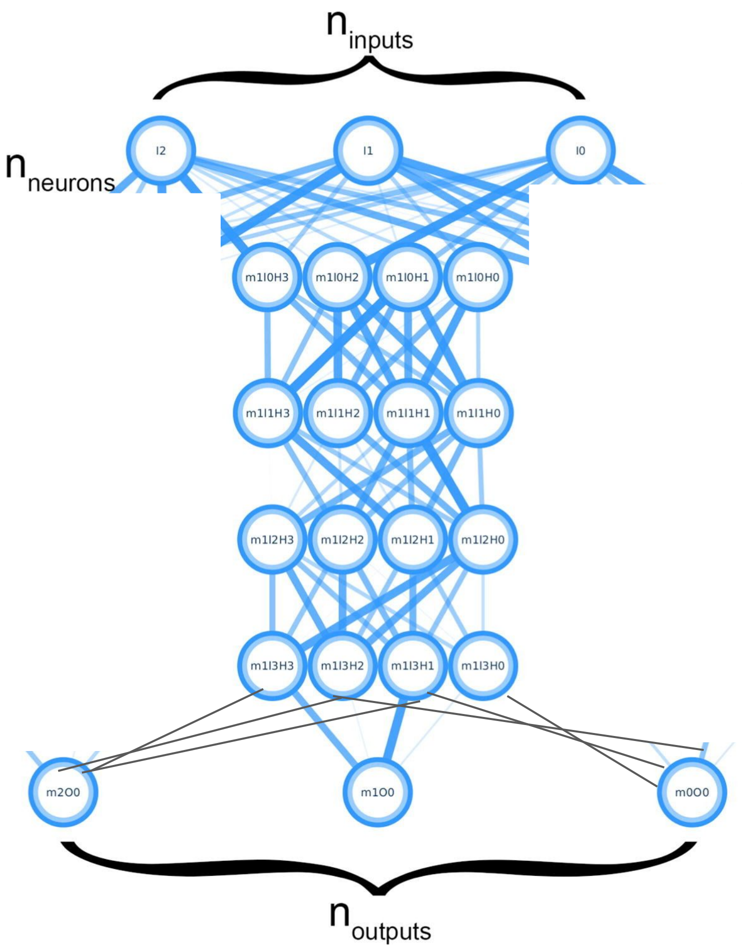
Network is run every 80ms (camera sampling rate).

With the given network architecture, computing 200 predictions took approximately 60 ms, which, given the interframe time (80 ms) is manageable in real-time operation.



Model

Using a single block for all 200 predictions runs faster but had worse performance.



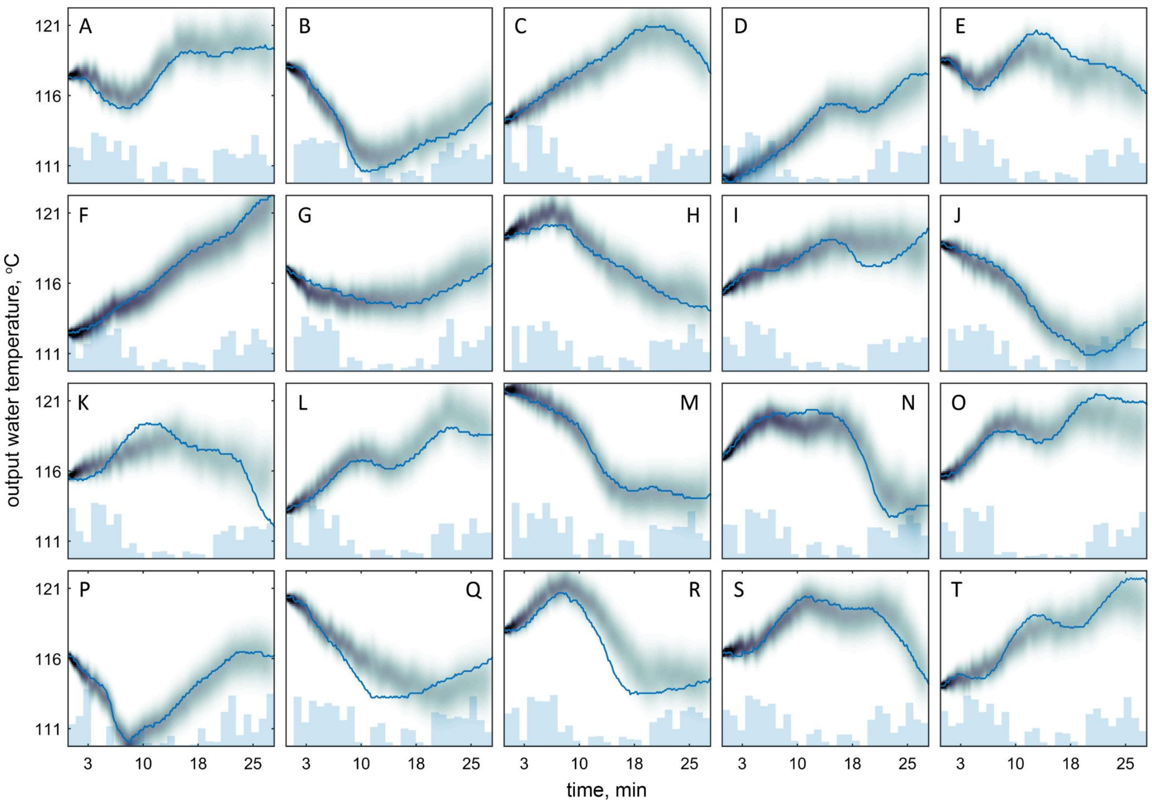
Training and test data

The training dataset spanned a time interval of 6 h, with approximately 280,000 flame images and 2200 entries from the boiler measurement system.

Test data was collected from a separate 6h interval

Results

The maximum time-ahead of approximately 28 min was established based on the errors the network produced as a function of time-ahead. Time-ahead values above 28 min seemed to produce unacceptably high errors. This indicates that the proposed network architecture was unable to find feasible relations between output water temperature and the learning features for predictions for longer time horizons than 28 min



The blue lines show the actual measurements in 20 scenarios. Shaded areas indicate the probability density of predictions

Results

After a time-ahead of approximately 28 min, the RMSE of predictions was found to increase rapidly, with the predictions becoming unrealistic, in some cases unable to follow general trends. This is probably due to the typical cycle time of the boiler in the training data, which was 20–50 min. Most likely, the ANN learns typical operation patterns including cycle times.

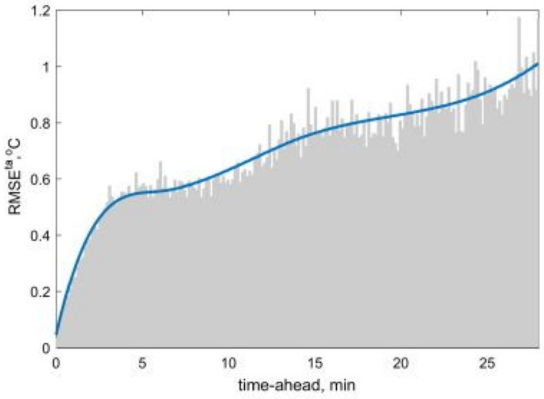


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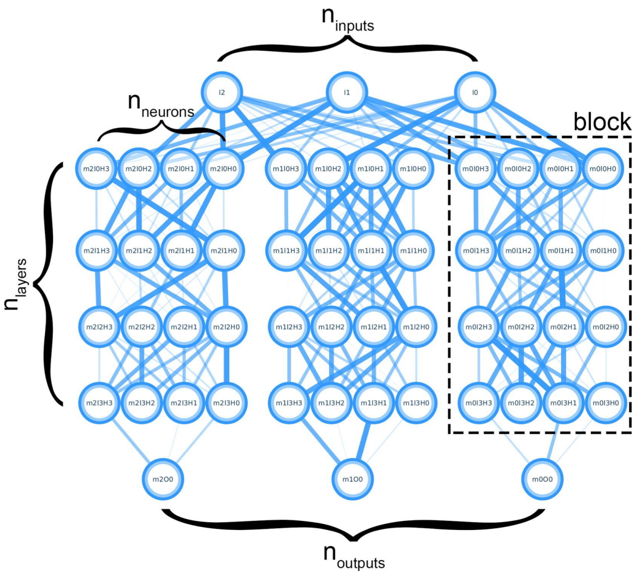
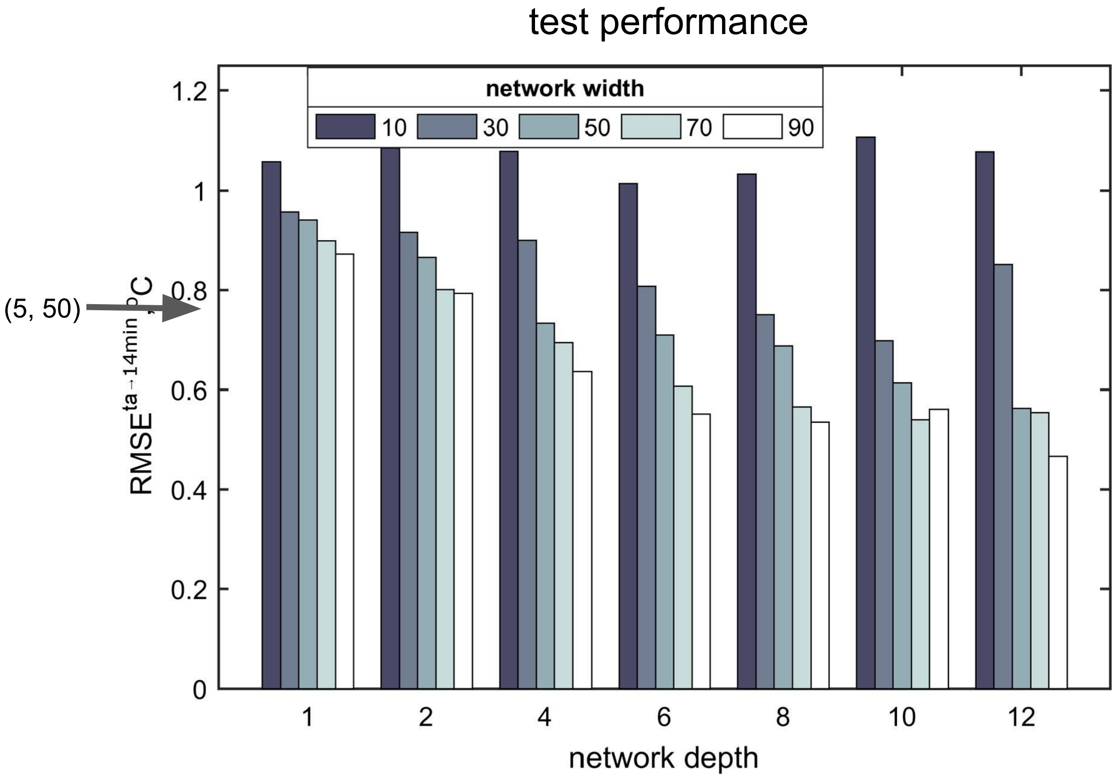
Fig. 8. Mean square error of the deep ANN-based prediction as a function of time-ahead. As seen, the error increases with the time-ahead up to $\pm 1\ ^{\circ}$C, which corresponds to a relative error of approximately $\pm 1\%$.

Would this model generalize well to other boilers?

Results

More computational expensive architectures can perform better.

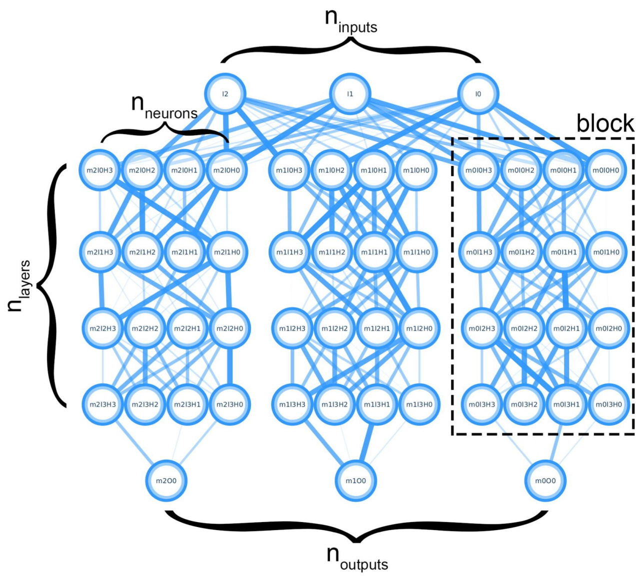




Results

“In many applications, artificial neural networks provide superior predictive power over other techniques. One significant drawback however is that ANN’s do not provide explanatory insight into the causal relations between the input and output parameters.”

Results

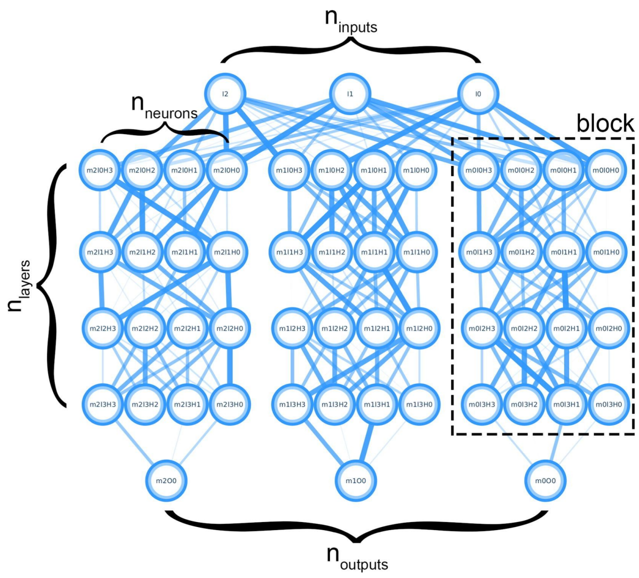


Sensitivity analysis can provide insight into the "black box" of an ANN by highlighting important and less important input parameters in the prediction system. The mean output sensitivity to the parameter x_k,S_k^{ta}, was defined as the mean of the partial derivatives [71] of predictions for a specified time-ahead over the test dataset:

$$S_k^{ta} = \frac{1}{n_{inst}} \sum_{ti=1}^{n_{inst}} \frac{\partial T_{ti}^{ta}}{\partial x_k}, \quad (4)$$

where x_k,$k \in [1,27]$ is the kth input.

Results



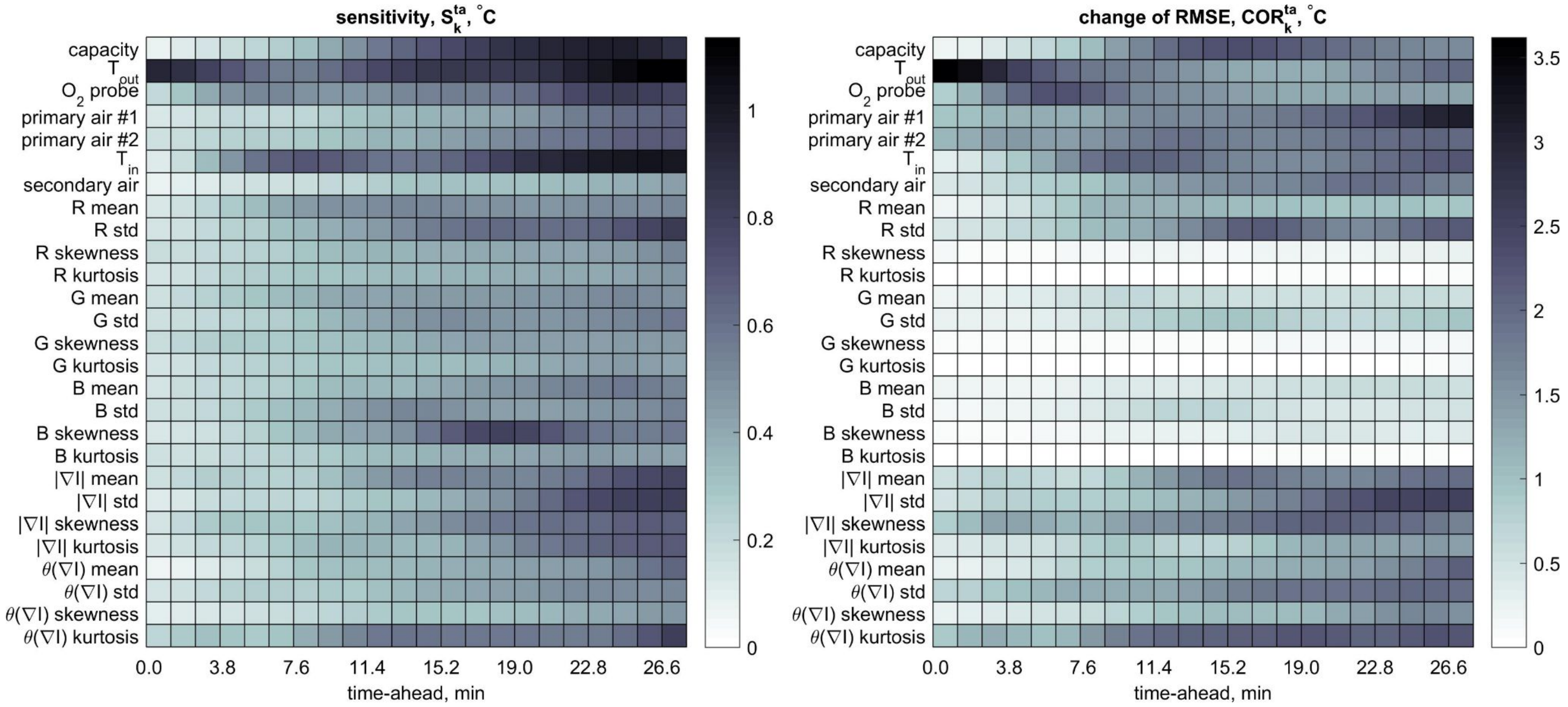
Another useful measure of the importance of network inputs is the so-called change of mean square error (COM) [71] that quantifies importance based on how much the mean square error of predictions is affected by excluding a particular input entirely from the calculation. By its original definition, COM is computed by re-training the network after the removal of one parameter at a time and comparing the resulting MSE to the value obtained with all parameters included. In this work, several modifications were made to the definition of COM. First, instead of MSE, the RMSE is used so that the temperature dimension of the measure is retained. Second, instead of re-training the network, the same training pattern was used, but the weight and bias associated to the selected input were set to zero, thereby removing the contribution of the input to the output. Re-training was omitted due to the sensitivity of the output to the network architecture, which is involuntarily changed when an input is removed from the feature set. The change of RMSE (COR) for a given time-ahead *ta* after removing the contribution of input x_k (COR_k^{ta}) was defined as the following:

$$\mathrm{COR}_k^{ta} = \mathrm{RMSE}_k^{ta} - \mathrm{RMSE}^{ta}, \tag{5}$$

where RMSE_k^{ta} is the RMSE for a given time-ahead evaluated after the contribution of the input x_k has been removed.

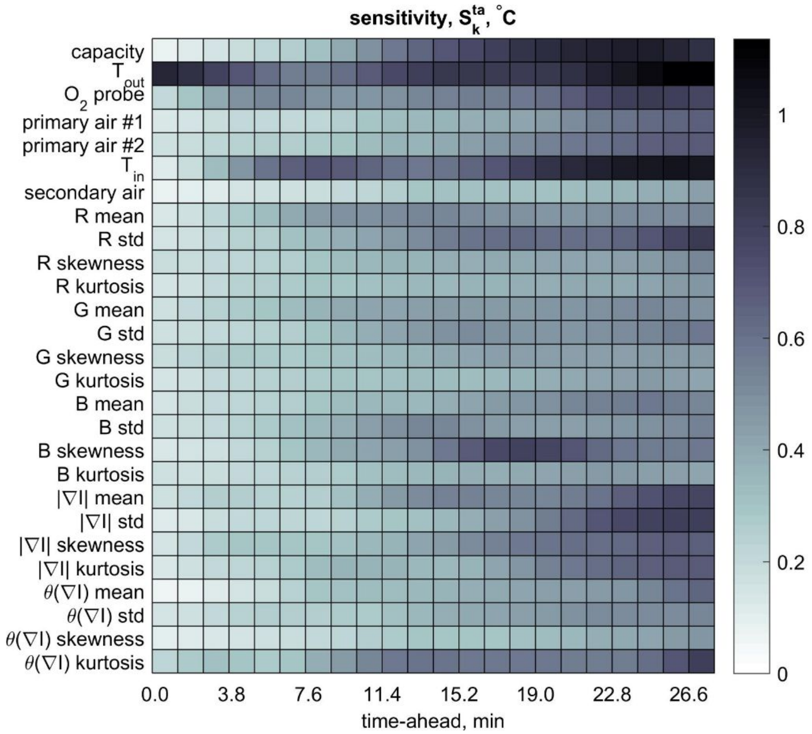
Results

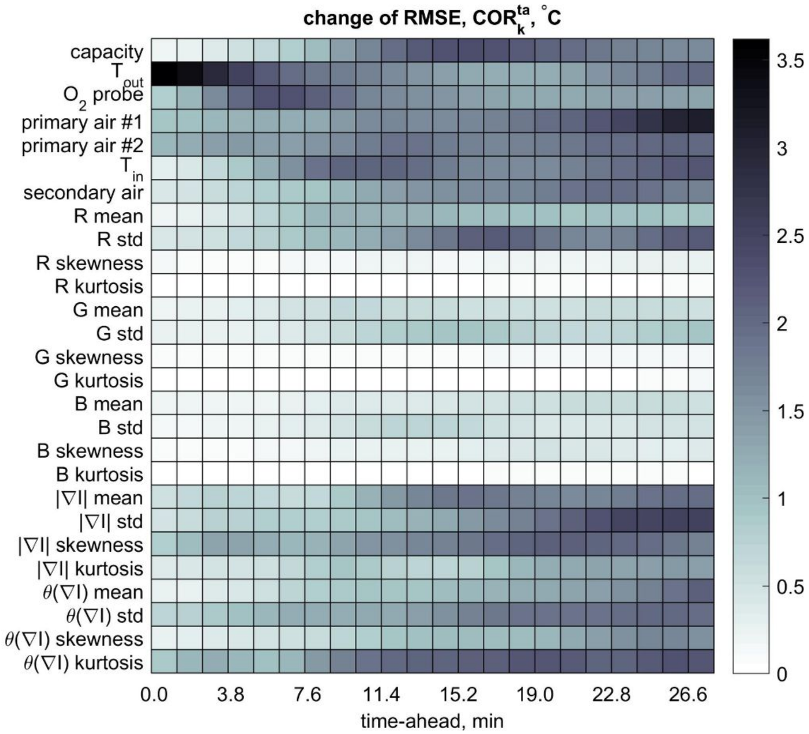
The two methods produced agreeing results in the case of many inputs—capacity, the instantaneous value of the output water temperature, the input water temperature, the standard deviation of the red channel intensities and several image gradient-based parameters were deemed as important by both techniques.



Results

“The internal relations of the NN revealed by sensitivity and COR analysis are somewhat unintuitive. For example one would not expect the low importance of parameters derived from the green and blue channel intensities, since the ratios of channel intensities carry pyrometric information about flame temperature, a fundamental physical property affecting combustion. Furthermore, the only relatively important radiometric parameter was the standard deviation of the red channel intensities—one would expect more sensitivity to the mean red intensity value, since it corresponds to the overall radiative intensity of the flame.”





4. Conclusion

This work investigated the applicability of a deep neural network-based prediction system to a 3MW nominal capacity, step-grate biomass boiler operated under varying, intermittent loads. The system took inputs from both the on-line measurement system of the boiler and a color camera monitoring the grate. The objective of the prediction system was to predict the output water temperature of the boiler in a multistep-ahead scheme in order to help issue warnings regarding potential future operating problems and facilitate robust control. Deep, fully connected neural networks were used in parallel to predict output water temperatures corresponding to different times ahead the present time. The system was able to produce predictions in real-time, in a rolling fashion —predictions regarding every time-ahead were available and continuously updated in real-time. The system was outputting both the expected values and prediction intervals of future water temperatures. The analysis of prediction errors showed that the error of short-term predictions (up to 1–2min ahead) was minimal. The errors grew steadily to up to $\pm 1\,^{\circ}\mathrm{C}$ for predictions approximately 28min ahead of the present moment. Further analysis revealed that the networks can be trained reproducibly in a fixed number of training epochs. The prediction errors depended on network depth and network width, indicating that the deep architecture was indeed utilized fully, without overtraining. Sensitivity analysis showed that the most important input parameters were the current value of the output water temperature for short-term predictions and several intensity- and shape-based image parameters for long-term predictions. The network was able to learn reasonable and intuitive relationships between the future values of output water temperature, physical principles affecting combustion and “operating experience” describing the periodicities of operation and the behavior of the flame in the characteristic phases of operation. The results demonstrate that flame imaging and deep neural networks can improve the response time and accuracy of predictive systems used in grate-fired biomass combustion.

Further Resources

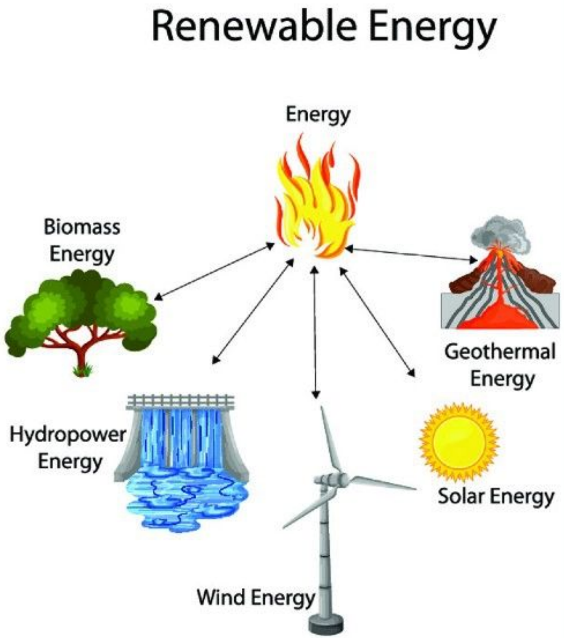
ML for renewables review article:
https://www.sciencedirect.com/science/article/pii/S0263876221003312

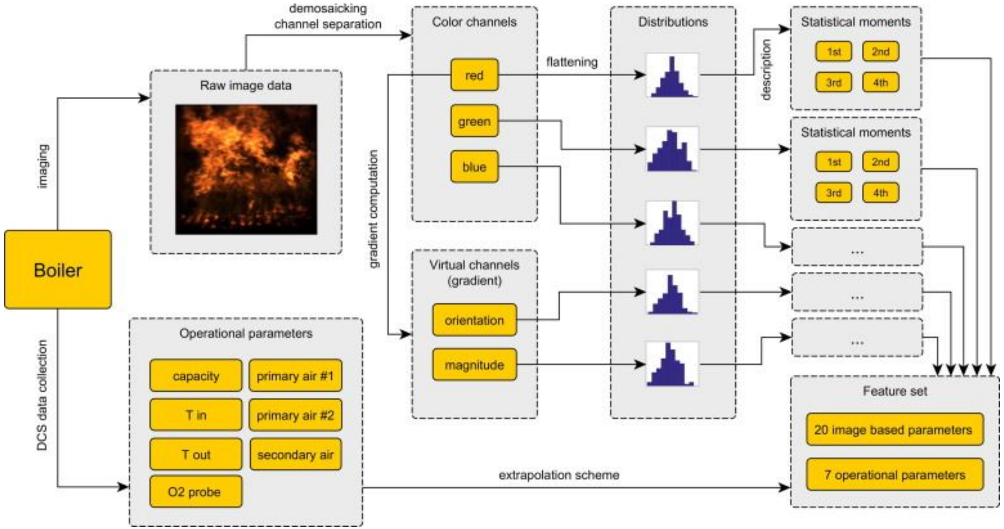
ML for nuclear review:
https://www.sciencedirect.com/science/article/pii/S1359028621000784

ML for nuclear waste review:
https://www.sciencedirect.com/science/article/pii/S0306454922004820

Short article on "floatovoltaics":
https://www.nature.com/articles/d41586-022-01525-1

Summary


Renewable Energy
Energy
Biomass Energy
Geothermal Energy
Hydropower Energy
Solar Energy
Wind Energy


demosaicking
channel separation
Color channels
Distributions
Statistical moments
1st
2nd
3rd
4th
red
green
blue
flattening
description
Raw image data
imaging
gradient computation
Boiler
Virtual channels
(gradient)
orientation
magnitude
...
DCS data collection
Operational parameters
capacity
primary air #1
T in
primary air #2
T out
secondary air
O2 probe
Feature set
20 image based parameters
7 operational parameters
extrapolation scheme