REFEREED PAPER

# INDUSTRY 4.0, ARTIFICIAL INTELLIGENCE AND ITS APPLICATION IN A BAGASSE-FIRED POWER PLANT

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## Abstract

This paper discusses the implementation of Industry 4.0 in the sugar factory specifically with regards to power generation. Key concepts such as cyber-physical systems, the internet of things, cloud computing and cognitive computing are explained. Examples of successes with artificial intelligence on boiler applications are described.

*Keywords:* artificial intelligence, industry 4.0, boilers

## Introduction

While you are reading this, artificial intelligence is already drastically altering your industry.

Business leaders are being forced to change their approaches to employment, employee engagement and innovation, as the Fourth Industrial Revolution reshapes the working environment. Machine learning is the driving factor changing the way every field operates, fundamentally. The global market for this transformation is estimated at $70 billion by 2020. Advances in customer service, manufacturing, healthcare, auditing, legal counsel, and insurance underwriting are already being pioneered by these algorithms (Schwartzkopff, 2017).

The sugar factory consists of a manufacturing process and a biomass power plant. Machine learning applications have been proven in both these areas; however, the current study focuses on the latter.

## Key concepts

Cyber-physical systems (CPS) are characterised by computer-based control integrated with the internet. The physical elements and digital software are interconnected although operating on different spatial and temporal scales. It is therefore a collection of computing devices interacting with each other and the real world via sensors and physical elements, e.g. actuators and motors in a feedback loop.

The Internet of Things (IoT) is a network of units enabled to connect and exchange data via the existing internet infrastructure.

Cloud computing is an information technology methodology that enables access to shared pools of configurable high performance computing resources. Services can be provided with minimal management over the internet.

Cognitive computing is technology based on artificial intelligence (AI) and signal processing. AI is the study of computations that make it possible to perceive, reason and act (Winston, 1993). Machine learning is part of this field and enables computer systems to learn by mapping relationships between variables in a multi-dimensional feature space.

Industry 4.0 refers to the fourth industrial revolution after computer and automation (seen as the third industrial revolution) via CPS. This is achieved by creating a smart factory. The physical processes are monitored and controlled by cognitive computing and the IoT which is turned into CPS with sensors and physical elements in a feedback loop with set objectives. A virtual copy of the physical world is created and decentralised decisions are made. Humans and these systems communicate in real time. Cloud computing forms part of this network to provide computing resources as need be.

## Case studies

Data analytics is a core capability of a smart factory. The following case studies illustrate how machine learning can be used to capture relationships between variables in a multi-dimensional space. The speed of execution is also shown and therefore it is ideal for reduced-order-modelling which ties in with creating a virtual copy of the physical world by means of cyber-physical systems.

Artificial neural networks (ANNs) were used since it is the most accurate and customisable machine learning technique.

ANNs are able to learn, self-organise and generalise. A training algorithm adjusts the weights and biases of the network during learning. The traditional modelling approach consists of a programmer with given inputs to a system, processing requirements and desired outputs. A set of step by step instructions are then followed to relate the inputs to outputs. ANNs do not require instructions, rules or relationships of data. ANNs determine the relationships between the inputs and outputs by looking at examples of input-output pairs, which is called learning. The ability to learn how to process the data to a desired outcome without a set of instructions is called self-organisation. Generalisation is the ability to calculate outputs from inputs that have not been seen before based on previous experience (Peacock, 1998).

ANNs are inspired by biological neurons in the human and animal brain. Neurons have three main components: the dendrites, cell body and axon as shown in Figure 1. The tree-like receptive networks of dendrites carry the electrical signals to the cell body. The cell body sums and thresholds the signals. The axon is a single long fibre that transmits the signal to another neuron's dendrite via a synapse. The mathematical equivalent of a single neuron is also shown in Figure 1. The scalar input $p$ is multiplied by the scalar weight $w$. The other input 1 is multiplied by a bias $b$ and added to the product of $w$ and $p$. The output from the summer is passed through a transfer or activation function to give the output from the neuron, $a$. In relation to its biological counterpart: the weight $w$ corresponds to the strength of a synapse, the cell body is the summer with activation function and the output, $a$ is the signal on the axon (Hagan and Demuth, 2014).

ANNs are formed by multiple layers of multiple neurons. The first and last layer is called the input- and output layer respectively with the ones in between called hidden layers.

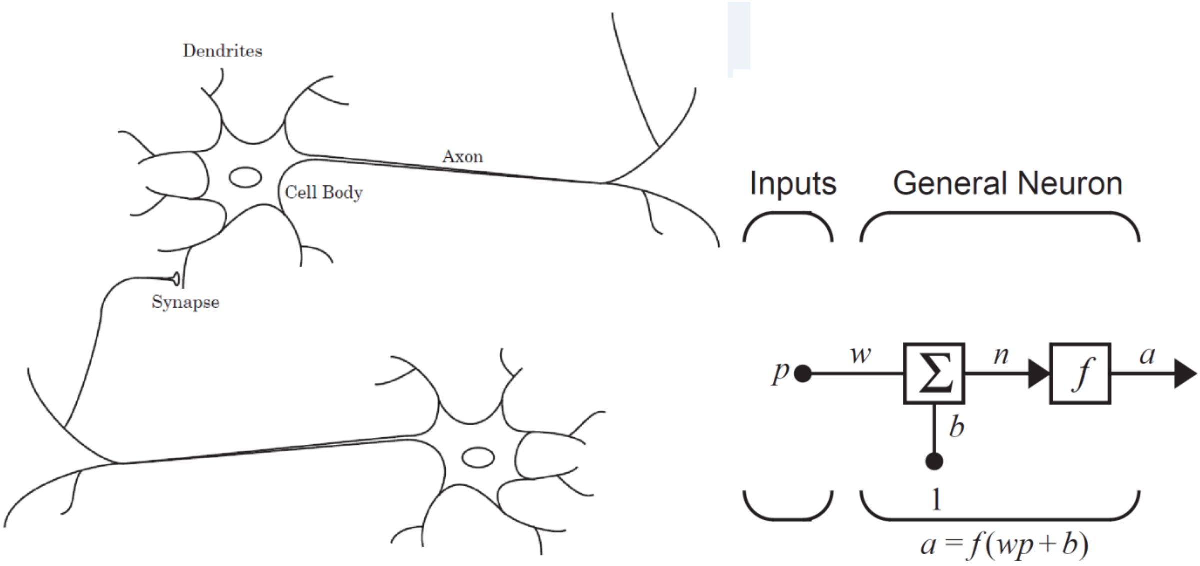


**Figure 1: Schematic drawing of biological neurons and single input artificial neuron (Hagan and Demuth, 2014).**

*Literature*

The application of ANNs in the sugar industry has been researched in the past. ANNs were used to model the boiling point elevation (BPE) of aqueous sucrose solutions. The resulting model outperformed the BPE correlation of Starzak and Peacock. It is remarkable, since this correlation was found superior to twenty existing BPE prediction methods from literature. The use of ANNs for image analysis in order to control continuous pan boiling has also been identified (Peacock, 1998).

*Chemistry integration*

Detailed chemistry is required in order to predict e.g. pollution emissions such as $NO_x$ from a bagasse-fired boiler in a computational fluid dynamics (CFD) simulation. The time integration of thousands of ordinary differential equations over different time scales compared to the main flow is required per cell of the computational grid. Therefore it is not feasible for industrial scale (CFD) simulations consisting of millions of cells.

ANNs were trained by John Thompson to predict the incremental species changes that occur in the fine structure regions created by the turbulence field in the boiler. These fine structures are the smallest eddies of the flow where mixing of air and fuel takes place on the molecular level and chemical kinetics governs the rate of combustion. The luminescent regions, measured by planar laser-induced fluorescence, in Figure 2, shows the fine structure regions measuring in only a couple of millimetres. The initial species composition, temperature and the residence time of the mixture in the fine structure were used as inputs to the ANNs.

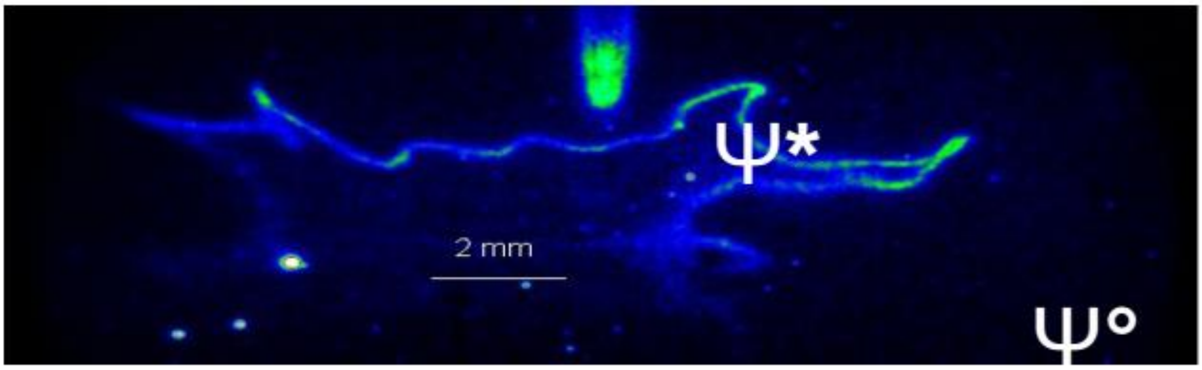


**Figure 2. Fine structure region in a fluid volume (Magnussen, 2009).**

It was proven that an ANN chemistry integrator can be used in order to solve detailed chemistry at the same speed as the current state of the art global reaction mechanism approach with an acceptable level of accuracy considering the minor species.

*Devolatilisation*

Devolatilisation is the starting point of the combustion process with solid fuels and especially important for biomass which consists of mostly volatiles. The Biomass Chemical Percolation Devolatilisation (Bio-CPD) model accounts for important affects that influence the accuracy of a simulation by taking into account the physical and chemical transformations of the fuel structure (Lewis and Fletcher, 2013).

A reduced-order model of the Bio-CPD model was implemented with ANNs by John Thompson in order to achieve ease of execution and computational cost reduction with regard to an industrial CFD application. The architecture, inputs and output of the ANN components are shown in Figure 3 where *T* is Temperature, *t* is time and *V* is volatile yield.

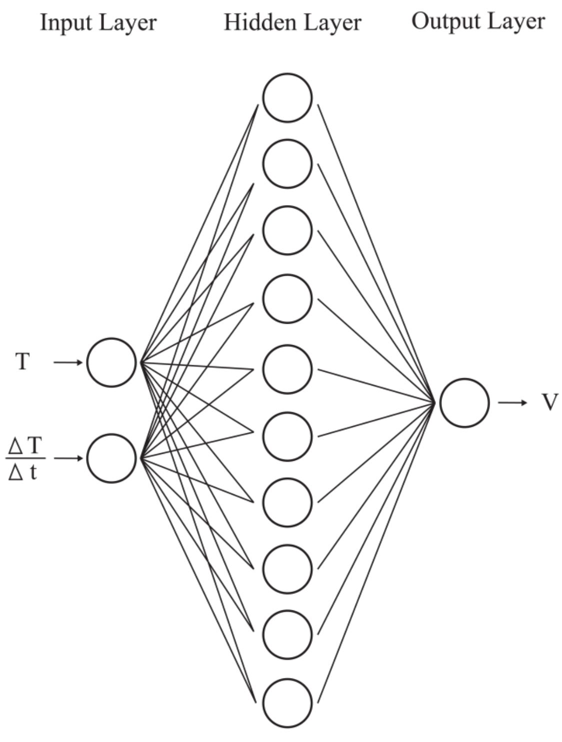


**Figure 3. Architecture of neural network.**

A dramatic speed-up of 450 times compared to the Bio-CPD model was achieved. The application in an industrial CFD simulation with bagasse showed an increased level of detail captured with regards to heating rate of the fuel particles.

The ANN approach can include data and an ensemble of models in the future to improve accuracy. More information can be continually added to the training data and therefore adaptability is another strength of this model.

*Diagnostics*

A data mining analysis was performed by John Thompson on an industrial scale biomass boiler co-firing sugarcane bagasse and furfural residue which operated intermittently at excessive final steam temperatures (415 to 430°C) when compared to the design steam temperature (400°C). The goal of the analysis was to find the cause of the high final steam temperatures and propose remedial action. The analysis comprised of using ANN, support vector regression and random forest machine learning algorithms to mine the operational data acquired from the boiler's distributed control system and generate a statistical predictive model.

A sensitivity analysis was performed on the boiler input parameters (fuel moisture, fuel density, fuel feeder speeds, induced draught fan speed, forced draught fan damper position, etc.) using the machine learning model, to find the inputs which cause the temperature excursions.

The model was able to accurately capture the boiler trends. The fuel moisture, fuel density and upward flow velocity in the furnace influenced the final steam temperature. The effect of fuel moisture and density on final steam temperature is shown in figure 4. As chute density increases, the steam temperature increases. The increased chute density is accompanied with a finer size grading fuel. The smaller particles burn higher up in the furnace.

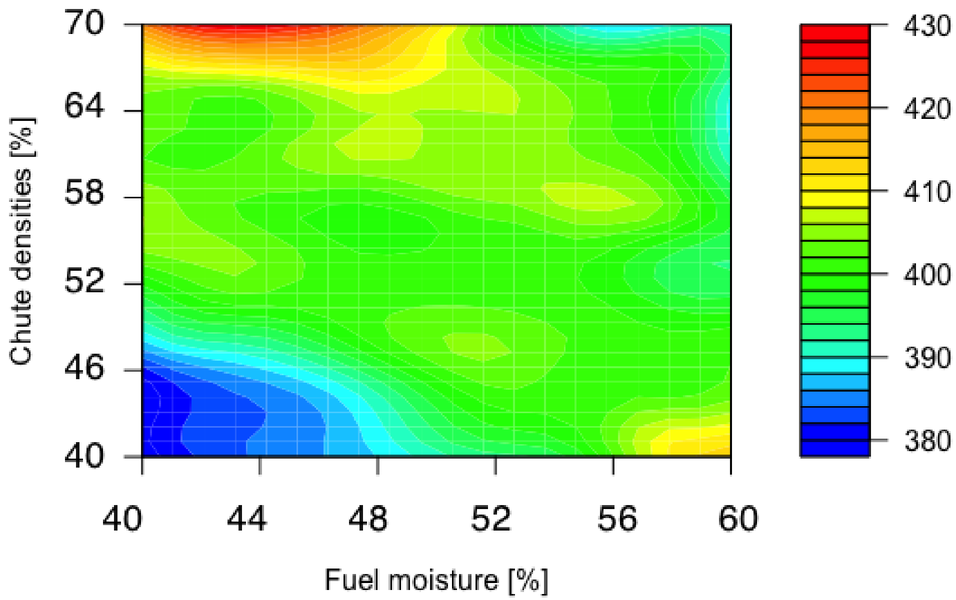


**Figure 4. Artificial Neuron Network (ANN) final steam temperature predictions for varying fuel moisture and fuel density**

## Work in progress

It was shown in the case studies that ANNs can accurately and in a computationally efficient manner capture very complex combustion characteristics and complete boiler plant behaviour. It was also shown that data can be mined with machine learning algorithms to establish unknown trends.

The following machine learning applications are the initial building blocks of an Industry 4.0 bagasse-fired power plant combining cyber-physical systems, the internet of things, cloud computing and cognitive computing.

*Model predictive control (MPC)*

The two steps involved with ANN control are system identification and control design. During system identification an ANN model of the plant to be controlled is developed. This can also be called a cyber-physical system. Secondly the ANN plant model is used to train the controller.

The ANN model of the non-linear plant is utilised to predict future plant performance. The control input is then calculated to optimize the performance over a specified future time horizon based on a certain objective. It is explained in Figure 5, where $y_r$ is the desired response, $y_m$ is the ANN model response, $u'$ is determined by the optimisation block to minimise the performance criterion over the specified time horizon, $u$ is the optimal input to the plant and $y_p$ is the process value from the plant.

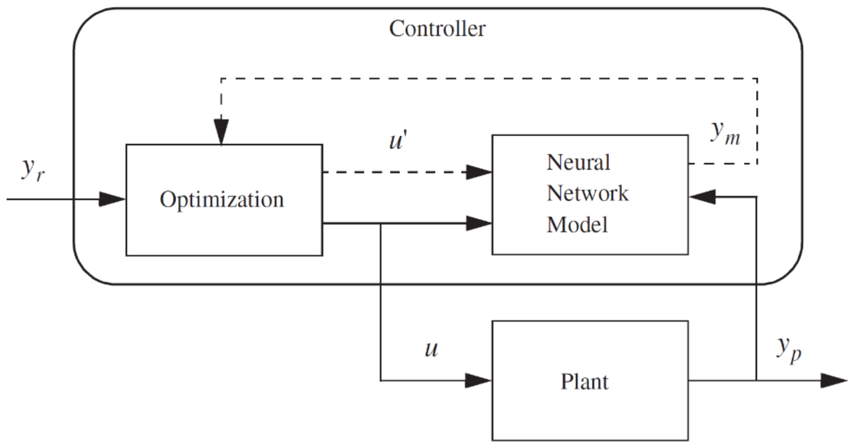


**Figure 5. Artificial neuron network (ANN) predictive control (Hagan and Demuth, 2002)**

The MPC learns continuously online by exporting data to the cloud via the internet of things, processing the data with cognitive computing (machine learning) on a high performance cluster and adjusting the architecture of the MPC ANN in order to achieve the set objective more efficiently.

*Predictive maintenance*

In contrast to preventive maintenance where a set plan is followed, predictive maintenance relies on data from sensors on equipment and the mining of this data with algorithms.

Methods of reducing the complexity of the data are used, e.g. principal component analysis. In the reduced form trends can be found with machine learning regression. Different stages of required maintenance can be identified within the developed model by means of classification.

A conceptual framework for this approach is shown in Figure 6. Data mining (DM) techniques are shown in the left portion of the figure. These are categorised as methods and models. The right part contains the main components of the framework which includes the activities and dependencies to create the model, namely problem setting, data selection and transformation, source system and staging, data set creation and data modelling.

During problem setting the most significant faults or failures of a particular machine are selected and relevant data identified with experts.

The data selection and transformation exercise consists of selecting the data for the training data set in consultation with the machine experts and by the cause-and-effect analysis of faults from the previous stage.

The source system and staging includes gathering and organising raw data from sources such as parameter logs e.g. machine settings, message logs and sensor data into a consistent structure for the following activities.

The data set creation section contains all the work to create a dataset suitable for the specific diagnostic algorithms used.

The last activity is data modelling where the model to predict the condition of the machine in real time is formulated. The model is formed with the data mining techniques, validated and tuned (Accorsi *et al.*, 2017).

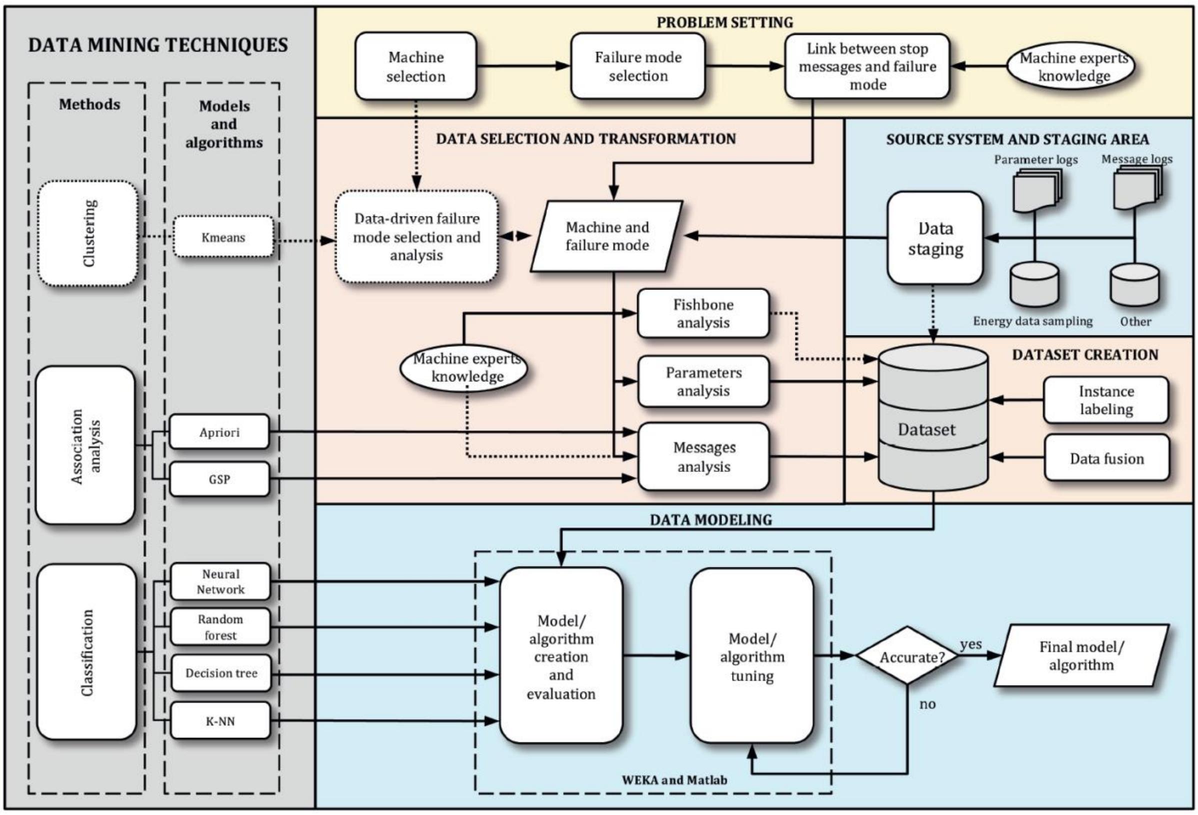


**Figure 6. Predictive maintenance conceptual framework (Accorsi *et al.*, 2017).**

The model is continually updated online as described for the MPC and predicts the health of the equipment and when maintenance is due. Therefore safety is improved and maintenance can be done more cost effectively.

## Conclusions

Case studies were presented which show that ANNs can accurately and in a computationally efficient manner capture very complex combustion characteristics and complete boiler plant behaviour. It was also shown that data can be mined with machine learning algorithms to establish unknown trends.

The initial building blocks of an Industry 4.0 bagasse-fired power plant were identified as a MPC and predictive maintenance. ANNs are utilised to create a virtual copy of the physical components of the plant which is used to predict future performance and controlled accordingly. Machine learning regression and classification are combined in order to mine sensor data and establish the health of the equipment to plan maintenance more effectively.

It is clear that the digitization of the sugar factory with AI has great potential towards improving efficiency. This will have financial and environmental benefits with regards to power generation.

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