# Real-Time Estimation of Bath Temperature in Aluminium Electrolysis Cells Using Temporal Neural Networks

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## Abstract

The bath temperature is a critical parameter to monitor in aluminium electrolysis cells as it significantly influences various phenomena within the cell, including side ledge and bottom freeze build-up, which can impact cell life. In today's energy landscape, there is growing pressure to modulate power input in potlines. This pressure is driven by the increasing reliance on renewable energy sources, which is often cyclical in nature, and from energy providers who wants to offset energy consumption peaks. Power modulations have a substantial influence on the bath temperature. Accurate and real-time bath temperature estimation hence becomes essential to monitor and manage optimal cell productivity conditions.

In this paper, we propose a virtual sensor based on Temporal Convolutional Neural Networks (TCN) to estimate bath temperatures in real-time. The proposed solution achieves a Mean Absolute Error (MAE) of approximatively 3 degrees Celsius, while never using any measurement of bath temperature as input. This level of accuracy is essential for effective power modulation and maintaining optimal bath conditions. It also allows for time-efficient scenario evaluation, leveraging a better decision making around modulations.

Our work highlights the potential of advanced Machine Learning (ML) techniques to perform real-time, accurate estimation of bath temperatures. By demonstrating the feasibility of this approach, we aim to pave the way for more modern aluminium electrolysis processes.

**Keywords:** Artificial Intelligence, Real-time, Bath temperature, Virtual sensor.

## 1. Introduction

Bath temperature is a critical parameter in the aluminium reduction process. Optimal aluminium generation occurs within a narrow temperature range between 960 °C and 970 °C. When the bath temperature is outside this thermal operational window, the metal productivity is reduced. Other than current efficiency, higher temperatures can reduce the lifespan of the cell by melting the side ledge around the cell and exposing the cell sides to lining erosion. On the other hand, lower temperatures can cause the superfluous bottom freeze that can cause uneven cathodic current distribution and uneven wear of the carbon blocks. In the industrial context, the monitoring of the temperature is done by manually inserting a thermocouple in the bath. This labor-intensive process is typically conducted once per day.

The energy landscape is undergoing a rapid transformation. The energy infrastructure is being put to the test by growing demands both from private consumers and the industrial sector. The increase in development of renewable energy sources such as wind and solar is changing the availability of energy at a given time due to their cyclical nature. [1] This phenomenon is exacerbated as energy demands vary during the day, corresponding to peak demand in households in the morning and evening, and through the year as seasonal temperatures fluctuate (heating during cold winter days and climatization during heat waves). Power companies are starting to create incentives to encourage the consumers to offset energy consumption during peak demand periods. One of these incentives is modulating the prices, lowering it during low-demand periods and increasing it during high-demand periods.

In the aluminium industry, power modulations offer a strategic approach to minimize energy-related expenditures. The goal is to reduce power consumption by decreasing the potroom current intensity during peak consumption periods, where prices are at their highest, and take advantage of off-peak periods by increasing the intensity. Since aluminium smelting is inherently energy-intensive, optimizing energy consumption by modulating the potline intensity can result in substantial cost savings. However, modulations can have a significant impact on the thermal balance of the cells. During lowered intensity, cells will cool, and heat-up during high intensity periods, creating substantial changes in bath temperature. Reaching temperatures too far out of the thermal operational target can have devastating consequences for cell performance and longevity.

To ensure that the bath temperatures of the cells will remain within an acceptable range before applying modulations, different algorithms can be used to estimate the behaviour of the bath temperatures during modulations. One approach is to create a physical model. A physical model is composed of mathematical equations that describe the thermal dynamics of the cells, including heat transfer, conduction, and radiation. In the case of the aluminium reduction process, a physical model would incorporate factors such as the cell's geometry, material properties, and operating conditions to accurately predict temperature fluctuations. The main advantage of this approach is that if the model is complex enough (encodes enough physical interactions), it can give estimates close to the reality. On the other hand, these algorithms are quite computationally expensive. Depending on the model, it can take more time to simulate than the simulation horizon, rendering it hard to use in real time, or at scale.

While using physical models provide more explainable results, using neural networks is also a viable approach. Neural networks are a type of machine learning model inspired by the structure and function of the human brain. At their core, neural networks consist of layers of interconnected nodes (neurons) that process and transmit information. One of the key advantages of neural networks is their ability to learn from large amounts of data, uncovering underlying patterns and relationships that might be difficult or impossible for humans to discern on their own. Despite requiring more learning time, once trained, neural networks can operate at high speeds, making them suitable for real-time applications. Moreover, advancements in neural network architectures have led to the development of specialized models tailored for processing time series data [2]. In this study, we employ the Temporal Convolutional Neural Network (TCN) architecture [3], which has been shown to excel on key benchmarks since its introduction in 2018, surpassing established techniques such as LSTM (Long-Short-Term Memory) networks [4], previously considered industry standards.

This paper aims to demonstrate the potential of neural networks for real-time estimation of bath temperature. For the context of this paper, the threshold of a reasonable model for bath temperature prediction was considered to be below 5 °C.

Finally, further work will be needed to access the ability of the model to generalize between a variety of cell designs and technologies.

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