

**PREDICTION OF CRITICAL PARAMETERS FOR
AUTOMATION OF KILN PROCESS USING DNN
REGRESSION**

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Degree of Master of Science in Industrial Automation

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DECLARATION

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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Abstract

Cement kiln, the most energy consuming unit of a cement factory, carries out the clinker manufacturing process, which must be operational with stable conditions to achieve consistent clinker quality and maximum production rate.

In order to maintain smooth and stable conditions inside the rotary kiln system (RKS), some process control parameters should vary within their desired ranges. This is achieved by doing some adjustments to the kiln control variables. In most of the cement plants, this overall control can only be achieved by manual control by operators.

The physicochemical and thermochemical reactions of the RKSs are not yet well understood due to their complexity. Therefore, the behavioral patterns inside the kiln cannot be determined exactly by the operators. Sometimes they end up with wrong decisions for control variables, which can cause the RKS to become unstable and cause huge losses to the cement company.

Few automation research studies have been conducted for continuous prediction of control variables for kiln process. However, not all of them address the actual inefficiencies that occur in processes, equipment, and the entire system by recognizing kiln behavioral patterns. Therefore, the automation of clinker production processes with proper prediction model is necessary and it helps to increase production, improve product quality, reduce production costs and operator interventions.

This research study is to predict critical control variables such as fuel rate, kiln speed and waste gas fan speed for given RKS parameters to maintain desired process condition inside the RKS. The RKS of Siam City Cement Lanka Limited is used as the case study. A regression based DDN model is implemented and trained for the best accuracy by adjusting hyperparameters. Model evaluation is done until obtaining a minimum error. The results of the model validation in real time scenario are also presented and discussed.

Keywords— Clinker Manufacturing; Rotary Kiln System; Deep Neural Network; Regression Model; Machine Learning; Kiln Behavioral Patterns; Kiln Process Automation

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LIST OF ABBREVIATIONS

Abbreviation	Description
RKS	Rotary Kiln System
AI	Artificial Intelligence
DNN	Deep Neural Network
PLC	Programmable Logic Controller
SCADA	Supervisory Control and Data Acquisition
ML	Machine Learning
BZT	Burning Zone Temperature
LSF	Lime Saturation Factor
SR	Silica Ratio
NO _x	NO and NO ₂
DC	Direct Current
AC	Alternative Current
SAT	Secondary Air Temperature
BET	Back End Temperature
HFO	Heavy Fuel Oil
AFR	Alternative Fuel Resources
MPC	Model predictive control
PID	Proportional, Integrative and Derivative
ANN	Artificial Neural Network
NN	Neural Network
TSK	Takagi Sugeno Kang
NFC	Neural fuzzy controller
SOP	Standard Operation Procedure
MIS	Management Information Server

CT	Current Transformer
CSV	Comma Separated Values
KNN	K - Nearest Neighbor
API	Application Programming Interface
MAE	Mean Absolute Error
MSE	Mean Squared Error
R ²	R - Squared Error
RMSE	Root Mean Squared Error
SSR	Squared Sum Error of Regression Line
SSM	Squared Sum Error of Mean Line