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

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DECLARATION

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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	Artificiel 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
NOx	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
R2	R - Squared Error
RMSE	Root Mean Squared Error
SSR	Squared Sum Error of Regression Line
SSM	Squared Sum Error of Mean Line

1. INTRODUCTION

Kiln operation is a complex process which consists of a set of activities that require proper technical knowhow. The fundamental process in the clinker production is to heat the raw material (limestone powder) mix in a kiln. Rotary kiln system (RKS) which has complicated nonlinear dynamic equations, conducts both physical and chemical reactions to provide final output. Many of the current variables are not considered in existing equations and the corresponding equations are not completely and accurately derived. Obviously, it is a massive challenge to design a controller for a RKS since the nonlinear and complex behavior of the kiln process [1][2].

As cement is the final product of a cement manufacturing plant, the final output from the RKS is called clinker. Sustaining an optimized process during the production leads to a high-quality clinker production and also, financial gain to the factory. These benefits can be achieved by introducing a control system for the RKS which is most appropriate and compatible. The production of over-burnt or under-burnt clinker is not expected from the RKS. The output clinker quality is affected by certain factors such as BZT (burning zone temperature), shape of the flame, SAT (secondary air temperature) and waste gas fan speed etc. [1].

Most of the cement plants around the world are operated with the direct contribution of the kiln operators who are experienced and knowledgeable. Therefore, to have an accurate knowledge of the kiln process and every situation and condition inside the RKS is very important for a kiln operator. [1]

Recently, many AI techniques have been increased the interest in research because of its advance features such as high efficiency of processing big data and ease of analysis etc. Deep learning is an artificial intelligence (AI) technology which can be used to extract high-level data features by obtaining hierarchical relationship between the input, output and hidden layers. Accordingly, deep learning model training is continued until the prediction errors are minimized [2].

Obviously, machine learning models do not require an exact model of the plant. Using a DNN model it can achieve remarkable stability and product quality of kiln process. [1]

Each cement kilns have a capacity of 1100 ton clinker/day and belongs to the company Siam City Cement (Lanka) Limited, Sri Lanka which are continuously manually controlled by process operators is considered for this work.

1.1 Problem Statement

Maintaining a stable condition throughout clinker production process is a mandatory requirement for the RKS. There are several process parameters are defined which should be maintained within defined operating ranges to achieve a stable condition inside RKS. Most of the kilns are operated by human operators who should have an expertise knowledge about the kiln operation using a PLC & SCADA system. With the complexity of the process there is no exact way or operational guide for the process control. The RKS process is totally depend with the decisions taken by the process operator. But the clinker production process can be interrupted by,

- Incorrect actions provided by inexperienced process operators
- Wrong decisions taken under critical signal failures

Which may lead huge financial losses to the cement company. Some of the major losses are,

- Production loss due to cost for restart the process
- Unnecessary electricity power wasting to restart the process
- Thermal energy loss
- Rejection of clinker batches during quality assurance

There are several control models have been developed to control preheater RKSs. These models have their own advantages and disadvantages but none of the models had considered learning based DNN regression approach to predict critical control variables for the kiln operation.

The motivation of this research is to develop a DNN regression model incorporating the critical control variables (fuel rate, kiln speed and waste gas fan speed) in to one model. The biggest challenge in this type of modelling is achieving computational efficiency while training the model using large number of data and real-time validation of the model in the actual scenario.

A model will be more useful if it is made available as an external expert system that can be integrated to the existing PLC & SCADA system

1.2 Research Objective and Approach

An external controlling system for RKS which can be automated the manual task provided by the process operators is real beneficial and it can be integrated to the existing PLC and SCADA system via the existing distributed peripherals.

The main objective of the research is:

- Implement an automated optimum operational model to predict fuel rate, kiln speed and waste gas fan speed to maintain good performance inside kiln during clinker production to achieve standard quality of clinker.

In addition to that, following benefits can be achieved by the work,

- Avoid hands on errors happen from operators.
- Reduce human intervention, save man hours from operating process parameters.
- Reduce unnecessary maintenance requirements of kiln instruments due to poor performance

1.3 Thesis Outline

The structure of the thesis can be depicted as follows. Chapter 2 describes the background details of the cement production, kiln operation, process parameters and controlling variables that define the overall operation about of the RKS and its controlling strategy. Finally, applications of ML for existing industrial process control systems are discussed, as well as some related works of kiln process control also discussed.

Chapter 3 represents the methodology of the research study illustrated with diagrams detailing the architecture of the predictive regression model and its implementation.

Chapter 4 presents the predictive outcome and model evaluation. The results are validated and discussed, taking into account the regression metrics and the loss function. Also, the real-time validation of the developed model is done using one of the RKS in Siam City Cement (Lanka) Limited.

Chapter 5 gives the conclusion and other achievements in the research study followed by for future improvements and limitations.

2. BACKGROUND AND RELATED WORKS

2.1 Background

Cement production is a complex process which includes chemical and physical reactions during the transformation of raw materials in to the final product. Furthermore, the clinker transformation process, which has a critical impact on energy consumption and production costs, involves the fossil fuel combustion reaction and the complex heat transfer from the raw material to the hot combustion gases. The process includes mixing and separating solids and liquids at different compositions, temperatures and pressures. Therefore, there is an urgent requirement to use computer based modeling to simplify the complex operation [6].

Cement production quality is totally depending on the raw material and the kiln operation. The kiln control system is responsible for producing the maximum quantity of clinker with the specified quality and minimum cost. The quality of the cement depends on many control parameters. The standard compositions of the basic components determine the most important qualities of cement; strength, settling time, heat of hydration, expansion etc. The free lime content (FCaO) also influences the quality of the final product [7].

Controlling a RKS is always a challenging task for kiln operators with the complexity of the process. Nowadays, having a computerized kiln control system is not an optional, practically it is a mandatory requirement with complexity of the kiln operation and the far-reaching consequences of disqualified clinker production, unstable operating conditions, production shutdowns and quality deviations. [5].

The use of modern technology can fix many problems encountered in the operation of the RKS. However, some kiln control loops are available, such as the fuel burner draft with features that go far away the capabilities of traditional kiln process controllers. Kiln operators usually switch such control loops to manual mode due to uncertainty situations of the process. Sometimes, their inappropriate control strategies may lead to an unstable kiln operation, clinker quality reduction, less clinker production rate and limited kiln performance [4].

AI based controls are able to provide advanced features as well as more capabilities to improve the productivity and product efficiency of process automation. When it comes to the cement industry, which is a high-energy intensive process, AI-based controllers have a lot to gain compared to other technologies. Most likely AI based intelligent control is a reality for many industries, specially process industry, and many cement plants all over the world adhere with this new concept [3].

2.2 Kiln Process

The kiln is a long, cylindrical tunnel where its diameter and length decide the production capacity of the cement factory. Usually, the dimensions of a rotary kiln are around 60m of length and 4m of diameter. The basic process is, raw material is inserted from the kiln inlet and transferred towards the kiln outlet along the kiln at a very slow speed. The input material (limestone powder) is included of carbonates and silicates combustion gases. The kiln shell has a slight tilt around its axis from the kiln input side to the output side. The raw material & clinker then slides slowly towards the cylinder output. The burning process is done in following places,

- Pre-heater
- Kiln
- Cooler

Hot gases generated inside the kiln during the process are used to preheat and completely dried the raw material before feeding it into the kiln. The main outcome of preheating process is to dry raw material by removing moisture and break up the silicates particles. Furthermore, preheating process conducts some partially calcination of carbonates in the raw material.

Inside the kiln main burning action is done at back end and burning zone. The main baking takes in place at the burning zone. At the area of back end, the raw materials are calcined before the main baking. Maintaining an increased back end temperature than the standard target, bakes the raw material quickly before entering the burning zone. Also, decreased back end temperature causes to the inverse effect. Kiln ID fan sucks the air inside the kiln through the preheater which affects the flame direction and the path of the combustion gases. The burner is installed to provide a controlled flame which facilitates the required process temperature, around 1400 °C is located on the other end of the kiln. Secondary air is provided by the cooler fans located at same side of the kiln. This secondary air is generated while doing the cooling process of the clinker. The input air flow to the RKS is denoted by secondary air pressure.

The high temperature action performed to raw material at the burning zone is called calcification. Raw material is melted at the burning zone due to the high temperature and chemical reactions are done. CO is the main component of the combustion gas after the reaction. After that cement crystals are formed and come out from the kiln outlet which has a temperature around 1000 to 1200 °C. The formed clinker should be suddenly cooled at the kiln outlet using cooler fans.

This cooling process directly influences to the clinker quality. This burning zone temperature should be controlled critically for a quality clinker production. Unfortunately, the real temperature of the burning zone is difficult to measure due to direct expose to the flame and the back-end temperature can be used for the operation [1].

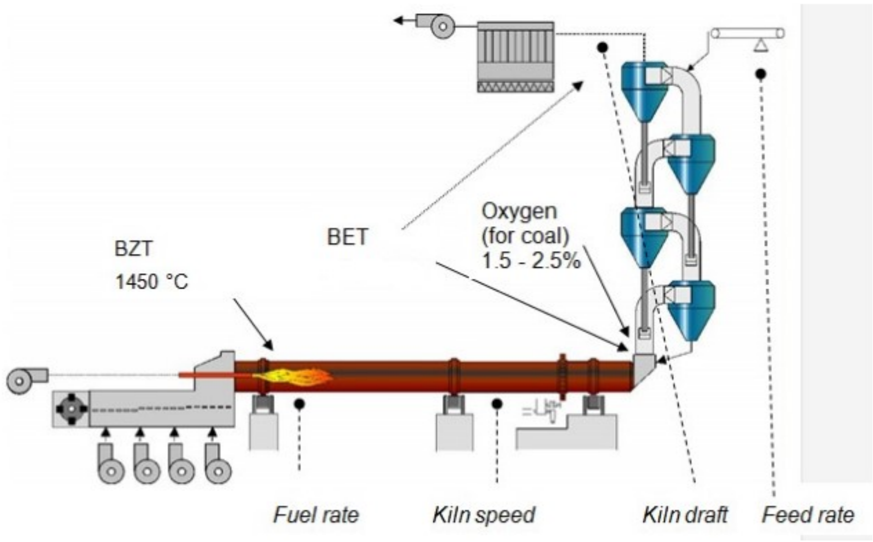


Figure 2.1: Diagram of Rotary Kiln System

2.3 Process Parameters

Kiln systems typically consist of many instruments, sensors, and measuring instruments. Those measured values are called control parameters which are the most important parameters for the operation of RKS. Control parameters which should be maintained around their specific targets, control variables are manipulated. Although there are many control parameters are defined, it can be identified some most important control parameters, directly influence to the process of RKS. Some of them are;

- Back End Temperature
- Burning Zone Temperature
- O_2 percentage of the combustion gas at the kiln inlet/ preheater
- Temperature and O_2 percentage of the exhaust gas outlet
- Bed height of the clinker bed [8][9]

2.3.1 Control Parameters

2.3.1.1 Burning Zone Temperature (BZT)

This reflects, the efficiency of clinker formation and transformation status of the raw material from C2S to C3S. Uncombined FCaO or free lime ratio of the clinker should be within ~0.5% to ~1.5% near the burning zone.

Frequently measured FCaO is the key indicator of the real BZT target, whether it is sufficient or not. Since the BZT targets are set only over a long-term period, typically it's sufficient to measure FCaO only for a one-hour or two-hour frequency.

Changes in the BZT target may be necessary due to changes in raw material composition, as change the burnability of raw materials with fluctuations in LSF, SR, magnesium and alkali content etc. Also, changes in flame characteristics that may occur as a result of multiple fuel consumption or different combustion conditions have a similar effect and may therefore require a change in the BZT target.

Mostly the BZT does not indicate an absolute temperature. But it provides some tips while controlling the RKS whether the BZT is higher or lower than the previously defined target [8][9].

2.3.1.2 Pyrometer Reading

Radiation measurements of the clinker and coating at the burning area provide the information related to its temperature. Pyrometer, which is a special-high temperature camera takes the radiation measurements inside the burning zone and converts those measurements into temperature values (see figure 2.2). Therefore, the temperature at the burning zone can be determined by measuring the radiation waves using the pyrometer. The combination of the colour and temperature can be illustrated as the table 2.1[9].

Table 2.1: A Rough Temperature and Colour correlation [9]

Colour	Rough Temperature
Lowest visible red to dark red	475-650 °C
Dark red to cherry red	650-750 °C
Cherry red to bright red	750-850 °C
Bright red to orange	850-900 °C
Orange to yellow	900-1100 °C
Yellow to light yellow	1100-1350 °C
Light yellow to white	1350-1550 °C

Figure 2.2: Pyrometer Snapshot of Inside the Kiln

2.3.1.3 NOx (NO and NO_2) of the Exhaust Gases

NOx is the gases produced during the kiln process which depends on the flame temperature and the available gases around burning zone and it is proportional to the flame temperature.

When BZT is reduced by considering NOx concentration of the combustion gases, then it is necessary to consider oxygen and CO concentration too, since the formation of NOx is directly affected to the CO and oxygen gases.

Furthermore, NOx emission is influenced by the fuel type (especially when burning alternative fuels) [8][9].

2.3.1.4 Kiln Torque

Kiln torque which is a short-term indication of the BZT, is proportional to the current, power or speed of the kiln main drive. The torque depends on the BZT and inside coating situation of the kiln. Torque is a very useful indication while operating the kiln. If the BZT rises the inside material becomes hotter and the required torque will be increased, while cold material causes for a low torque requirement [9][10]. Figure 2.3 illustrates the torque changes of a hot and cold kiln.

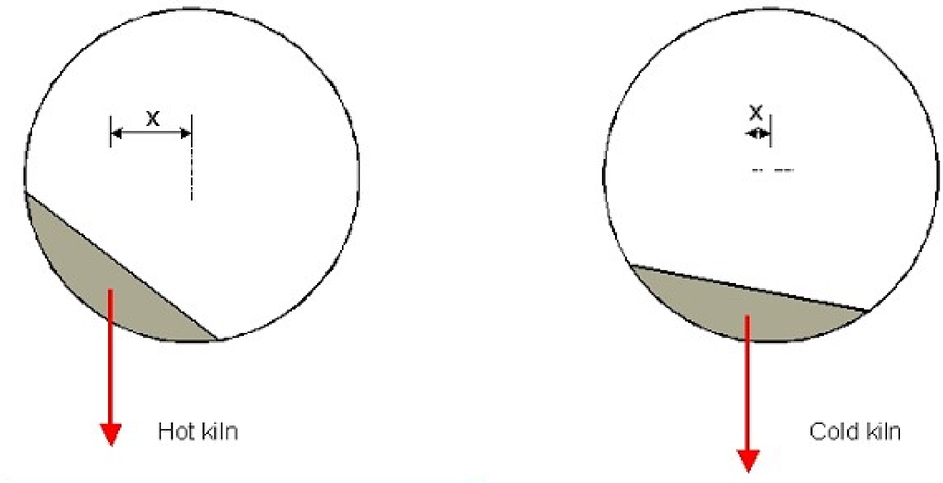


Figure 2.3: Torque of a Hot and a Cold Kiln [9]

2.3.1.5 Secondary Air Temperature (SAT)

SAT is coming in to the picture for RKSs which have grate cooler system which indicates the information of BZT. SAT is higher if the BZT is higher, since the released clinker is hotter (and vice versa). Furthermore, SAT is depended some more factors such as cooler operation, clinker granulometry etc. Therefore, the correlation between BZT and SAT does not valid for every situation [9][10].

2.3.1.6 Back End Temperature (BET)

BET is the of the exhaust gas temperature from the kiln inlet that enters to the pre-heater which is a major indication of the hot meal preparation status, before entering into the kiln. Usually the type of the RKS and the length to diameter ratio of the kiln is decided the BET range. BET is around 800 °C for wet kilns. Since the BET measurement is somewhat challenge to measure, usually, the preheater exit temperature is used as the BET which is easily measurable [8][9].

2.3.1.7 Oxygen Control

Excess air is a mandatory requirement for a better burning of fuels. This excess air inside the system, is measured by considering the oxygen concentration of the exhaust gas. Oxygen level maintaining is essential for high thermal efficiency and good combustion of the RKS.

Generally used oxygen targets at the kiln inlet for the usual RKSs are defined as per the table 2.2. Oxygen level requirement depends on factors, such as the type of RKS, fuel type (e.g. HFO demands low excess air with compared to the coal or AFR) [8][9][10].

Table 2.2: Generally Used Oxygen Targets at the Kiln Inlet (dry gas) [9]

Kiln Type	Gas	Fuel oil	Coal	Petcoke Solid AFR
Wet kiln	0.5 – 1.0 %	1.0 – 2.0 %	1.5 – 2.0 %	2.0 – 2.5 %
Lepol kiln	1.0 – 1.5 %	1.5 – 2.0 %	1.5 – 2.5 %	2.0 – 3.0 %
Preheater kiln	1.0 – 1.5 %	1.5 – 2.0 %	1.5 – 2.5 %	2.0 – 3.0 %
Inline PC kiln	2.5 – 3.0 %	2.5 – 3.0 %	2.5 – 3.5 %	2.5 – 4.0 %
Separate PC kiln	1.0 – 1.5 %	1.5 – 2.0 %	1.5 – 2.5 %	2.0 – 3.0 %

2.3.2 Control Variables

Control variables are adjusted in order to maintain control parameters close to the targets. In order to operate the RKS smoothly and efficiently, those control parameters should be maintained nearly closed to the target. For a better control of the kiln, it's necessary to maintain small deviations of the parameters from the target.

The main control variables as follows:

- Fuel rate to the kiln
- Raw material feed rate to the kiln
- Kiln draft (Waste Gas Fan Speed)
- Kiln speed [9][10]

2.3.2.1 Fuel Rate to the Kiln

Due to rise of the fuel rate:

- BZT high
- BET high
- Oxygen concentration low

(The reduction in fuel rate has the opposite effect).

According to that, if more fuel is fed into the system, the BZT and the BET rises and oxygen levels drop due to excess air consumed to burn excess fuel [9].

2.3.2.2 Feed Rate to the Kiln

Due to increase the material feed rate:

- BZT low
- BET low
- Oxygen concentration low

(The reduction in raw material feed rate has the opposite effect).

If the feed rate is increased to the RKS, first the temperature of the back end starts to drop. Once the high feed intake reaches the burning zone, BZT also begins to decrease. With this additional H_2O & CO_2 introduce into the system which may reduce the combustion air. This causes to a reduction of oxygen level in the exhaust gas since the since the exhaust gas remains constant [9].

2.3.2.3 Kiln Draft (Waste Gas Fan Speed)

Due to increase the draft in the kiln (waste gas fan speed):

- BZT low
- BET high
- Oxygen concentration high

(A small reduction of the waste gas fan speed has an opposite effect)

With the rise of the waste gas fan speed, more secondary air is supplied in to the kiln through the burning zone. It causes for a decrease of the flame temperature which results the drop of BZT. Even the amount of heat supply to the kiln by secondary air is high, small amount of heat is released in to the burning zone.

Furthermore, higher kiln draft causes for increase of both O_2 level and exhaust gas volume [9][10].

2.3.2.4 Kiln Speed

Due to increase the kiln speed (kiln drive speed):

- BZT low (temporarily)
- BET low (temporarily)
- Oxygen low (temporarily)

(The reduction in the kiln speed leads to an opposite effect)

With the increase of the kiln speed, moment of the material inside the kiln is get faster. As a result, all reaction phases move downward temporally, which leads the BET and the BZT to decrease. The sudden entering of the more meal in to the drying and calcining zone H_2O and CO_2 concentration of the air is increased, which causes for a drop of oxygen level.

Above effects are valid only for a few minutes, since an increased kiln speed reduces the filling level in the kiln (at a fixed feed rate). BZT, BET, and oxygen are restored when the entire kiln filling level is reduced [9][10].

2.4 Control Strategy

While controlling the RKS, an adjustment of one control variable has an influence on all other control parameters. It is usually necessary to set more than one control variable to maintain all control parameters nearly close to their targets. While doing this, correcting one specific control parameter, can lead to a deviation of an another.

Accordingly, a consensus needs to be found that reduces all the control parameter deviations. Type of the RKS decides behavior of the consensus which is introduced.

Furthermore, the selection of the control variables as well as the setpoints for them, to maintain control parameters within acceptable ranges are decided according to the general view of all RKS parameters that is exist for an instance [9].

2.5 Applications of ML Algorithms for Industrial Process Control Systems

2.5.1 Model Predictive Control (MPC)

MPC is used for proactive control of complex, non-linear processes. MPC is used to predict about future situations, while reaction-based control strategies, such as PID control, make their controls on historical and current system conditions as recorded by sensors. Therefore, an MPC controller needs an accurate simulation model of the process to generate reliable predictions.

Machine Learning is a subset of AI (see the figure 2.4). It enables statistical methods and algorithms that allow machines to automatically learn from their previous experience and data. That is, it allows the algorithm to adapt to system behavior. Deep learning is the evolution of machine learning that draws vision from the workings of the human brain. Deep learning technology, built on artificial neural networks is used to solve complex problems by using large, varied, less structured data.

Recently, the application of AI and ML to many fields in science has revolutionized some fields, such as neuroscience, robotics, and industrial technology which is increased the accuracy and precision of detection and prediction. Different classification and regression algorithms are available to make the right decisions for ML. Also, automated learning to perform integrated control functions is expressively interesting and of considerable practical importance to the AI field [16][17][18].

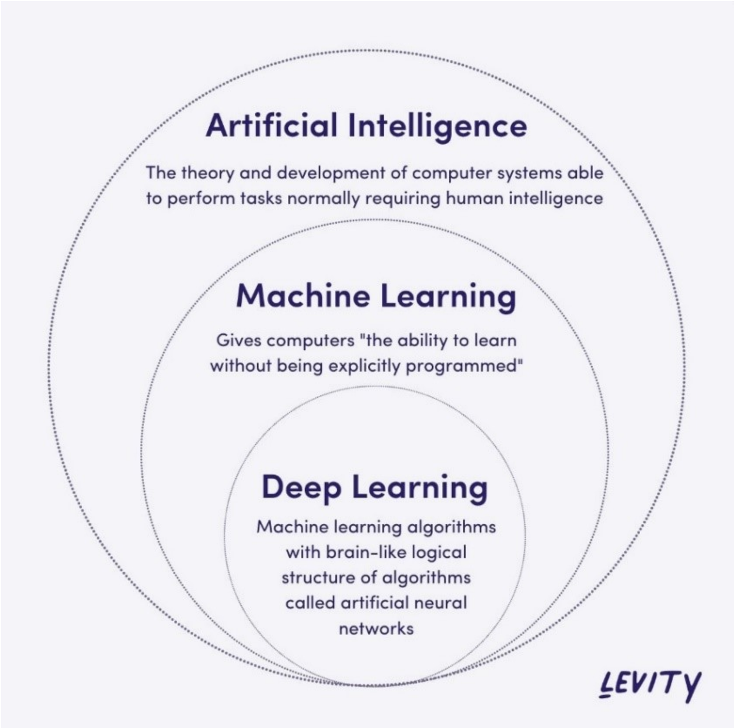


Figure 2.4: Subsets of Artificial Intelligence

2.5.2 Linear Regression

Linear regression is approach for modeling a combination of regression coefficients of one or more explanatory variables [13]. The coefficients are calculated using a technique called “generalized least square”. The linear regression is definite and the parameters are low, requiring no modification. Only modification required is splitting the dataset as training and testing [16]. Linear regression model in machine learning is presented in Figure 2.5

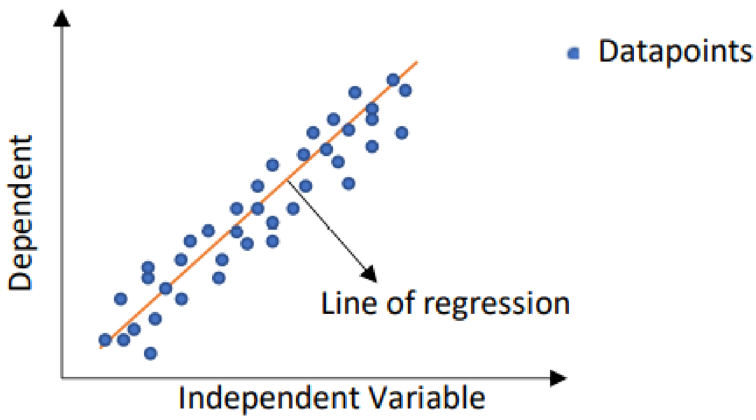


Figure 2.5: Linear Regression Modeling in ML

2.5.3 Artificial Neural Network and Industrial Usage

ANN which is an intelligent computational technique developed based on the field of biology in the human brain, called the Neural Network (NN) [14]. ANN is inspired by biological neurons which is known as a Deep Learning technique to build a model according to training data for make predictions using a neural network. ANN is very similar to the other typical ML algorithms, except the usage of multiple layers what makes it Deep learning [12].

ANN is a massive parallel computing system with a massive number of individual processors with including many interconnections. Some basic terms should be discussed in the field of ANN are input layers, hidden layers, output layers, hyper parameters, epoch, batch size, activation function and optimization function.

Input layers are the layers that retrieve inputs based on available data. Hidden layers which are used backpropagation to optimize the weights of the input variables to increase the power of the prediction of the model. Output layers consist with predicted outputs based on the available data from the input and hidden layers. Epoch is defined as the number of forward and backward data passes for the total training examples. Batch size is the number of training examples to the model per one forward/backward pass.

Activation function inaugurates nonlinearity behaviors to models to provide the capability to learn and perform more complex tasks to the model. Typically, a neural network without an activation function is considered as a linear regression model.

Optimization is a method used to minimize losses by modifying the properties of a neural network, such as weight and learning speed. In order to optimize neural networks, gradient descent technique is preferred.

Hyper parameters are the parameters that does not learn within model by itself. Also, those are passed as arguments to the model constructor of the steps in pipeline. Regression validation is used to fetch the best possible parameters for the model.

Typically, number of neurons, activation function, optimizer, learning rate, batch size, and epochs are considered as hyper parameters which use to tune the model [15].

2.6 Related Works

2.6.1 A Neuro-Fuzzy Controller (NFC) for Rotary Cement Kilns

In the particular work the advantages of neural-fuzzy network techniques are used to develop an intelligent control system for RKS. A NFC has been developed to control several RKS variables. The variables are BET, pre-heater temperature, O2 and CO2 inside the RKS. As an advanced control technique, a fuzzy control system is discussed to reduce operator involvement during the control process. TSK-type fuzzy controller which uses a neural network to optimize the controller is proposed. Real-time data obtained from a real cement plant is used to identify the plant model.

NFC can be learnt to control the process by updating fuzzy rules as well as the membership functions. However, there are some practical limitations and conditions that must be considered when designing the controller [1].

2.6.2 Internet and Fuzzy Based Control System for Rotary Kiln in Cement Manufacturing Plant

An internet-based fuzzy control system is proposed which is integrated with remote control of the cement plant. Fuzzy control is ensured a reliable operation with minimal downtime of the RKS. Internet based remote system ensures the control, diagnosing alarms occurs, maintaining and synchronizing different regulation loops of the RKS.

The introduced system has control capabilities of both operators in the main control room or via remote controlling which reduces downtimes. In this work, a new architecture is introduced for RKS which is based on the remote of a fuzzy control using internet access [8].

2.6.3 Intelligent Control for the Cement Industry

Intelligent control provides new capabilities to enhance the productivity and efficiency of process automation. In the process industries which are energy insistent, there is much to be gained by applying new technology to the cement industry. In this study, an architecture and some advance features of an operational hierarchical distributed intelligence system is introduced for the control of a RKS [3].

2.6.4 An Expert System Application for Lime Kiln Automation

In this work, a rotary kiln automation system is discussed that integrates a specialist system with adaptive loop controllers to automate kiln operation. This system is able to significantly improve the RKS performance.

As the previous attempts to build a general purpose mathematical model of the calcining process have proven not accurate, an expert systems approach to kiln automation allows the unique characteristics of each kiln to be considered. Features of expert system programs which are more flexible and allows kiln operators to easily modify the operation while any process changes. One specialist system for combustion control and another for product control is used which allows isolate operating of the both systems. This is beneficial even some of the equipment are not presented [4].

2.7 Literature Review Summary

Techniques Used	**Application**	**Advantages**	**Research Gaps**
Neuro-fuzzy controller	To control several control variables inside the kiln	Reduce operator involvement during the control process & intelligent control system for RKS	Parameters must be defined in a defined range. Limited operational conditions are defined
Internet and fuzzy based control system	Internet-based fuzzy control system has been developed for a cement plant to ensure the fuzzy control with the capability of remote control	Ensures the control, diagnosing, maintaining, troubleshooting and synchronizing different operational loops of the RKS while providing intelligent control	Does not fulfill all the process conditions provides by a human operator. Some control deviations may be occurred due to undefined conditions
Adaptive process loop controller	Expert system with adaptive loop controllers to automate RKS	Allow kiln operators to easily modify the automatic operation of the RKS while presenting some process or equipment changes	Separate controllers are required for combustion control and product control
Fuzzy Control++	Access to process bus over the internet and control remotely	Preconfigured control loops for the varies applications	Only compatible with Siemens Automation systems

3. MODEL IMPLEMENTATION FOR PREDICTION OF CRITICAL PARAMETERS OF KILN PROCESS

This chapter consists of five phases. These five phases convert raw kiln operation records into valuable intelligence information which are then used to implement the ML model to predict fuel rate, kiln speed and waste gas fan speed. These five phases of the research consist of distinct objectives to achieve the ultimate goal of this research, which predict optimum values for critical parameters.

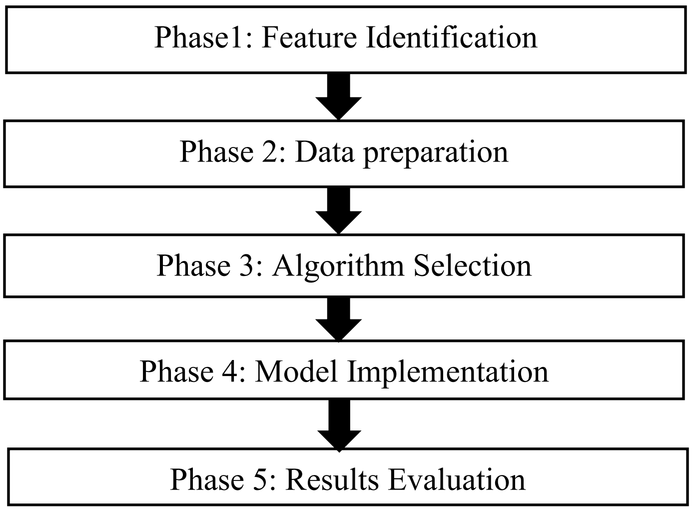


Figure 3.1: Five Phases of the Research Work

3.1 Feature Identification and Extraction

Process parameters that are most relevant to the research study are identified and extracted using following resources.

- Background study and literature review
- Holcim SOP manual [28]
- Discussion with Kiln operation experts

Following parameters are extracted as control variables and process parameters which are directly influenced to the stability of kiln operation, from the plant PLC and SCADA system which display 50+ parameters. Table 3.1 shows the two types of kiln operation features which are extracted.

Table 3.1: Two Types of Kiln Operation Features

Kiln process control variables	Kiln process parameters
Kiln feed rate	Preheater CO
Kiln rotational speed	Preheater Oxygen
Waste gas fan speed	Preheater Nox
Fuel rate	3rd Cyclone Pressure
Grate Drive Speed	3rd Cyclone Temperature
AF rate	4th Cyclone Pressure
HFO rate	4th Cyclone Temperature
	Kiln Hood Pressure
	Kiln Ampere

Control variables can be considered as independent variable whereas process parameters can be categorized as dependent variables. The table 3.2 displays the standard optimum ranges for the stable operation of RKS.

Table 3.2: Standard Optimum Ranges for the Stable Operation of RKS

Dependent variables		Independent variables	
Feature	**Kiln stable range**	**Feature**	**Kiln stable range**
Preheater CO	0 – 1000 ppm	Kiln feed rate	60 - 85 t/h
Preheater Oxygen	4 – 5 %	Fuel rate	3000 - 6000 kg/h
Preheater Nox	0 – 1000 ppm	Waste Gas Fan Speed	950 - 1150 rpm
3rd Cyclone Pressure	180 – 250 mmH_2O	Kiln Rotational Speed	1.2 - 2.1 rpm
3rd Cyclone Temperature	600 –. 700 ºC	Grate Drive Speed	6 – 9 storke/min
4th Cyclone Pressure	90 – 150 mmH_2O	AF rate	0 – 5300 kg/h
4th Cyclone Temperature	770 – 870 ºC	HFO rate	0 – 1000 kg/h
Kiln Inlet Pressure	25 – 40 mmH_2O	Waste Oil rate	0 – 1000 kg/h

3.2 Dataset Preparation

Once the Kiln operation features are extracted, data collection is performed based on that. Next the dataset is analyzed to verify the quality of the data which represents stable condition of the kiln operation. After each feature data are joined together, dataset is preprocessed to obtain a qualified dataset. Finally, the dataset is got ready for the model implementation.

3.2.1 Data Collection

Plant MIS is a data server that stores all operating data related to plant automation system. Fig 3.2 shows the image of the MIS interface.

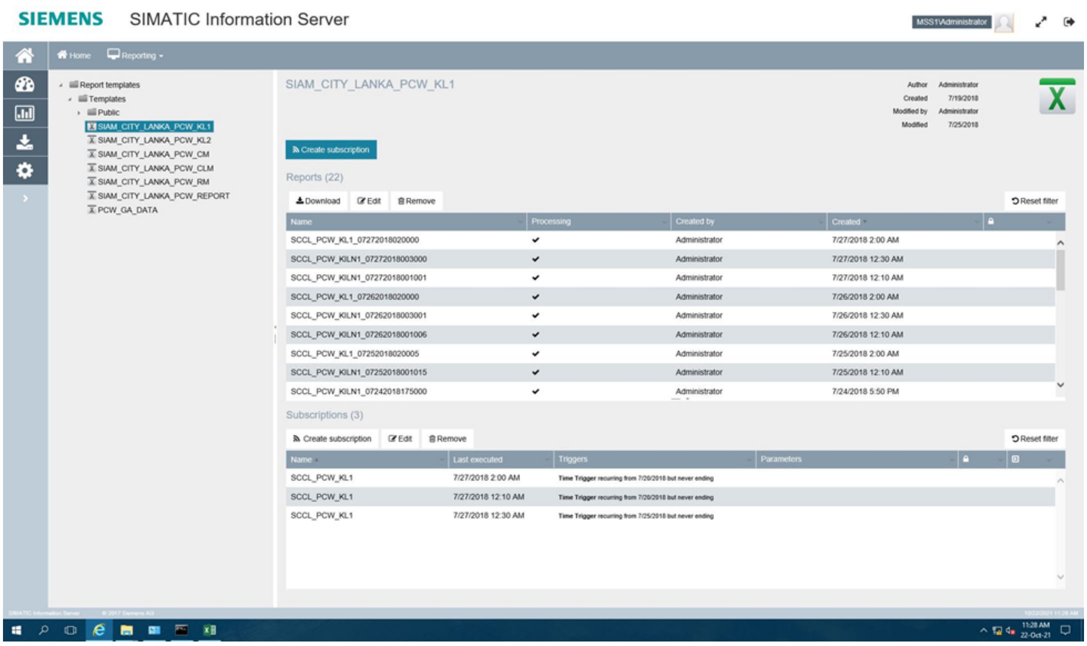


Figure 3.2: Siemens MIS Interface

MIS is integrated into plant PLC and SCADA system via large number of process tags which are configured to analyze specific process parameters in the cement plant. Fig 3.3 shows some of existing process tags.

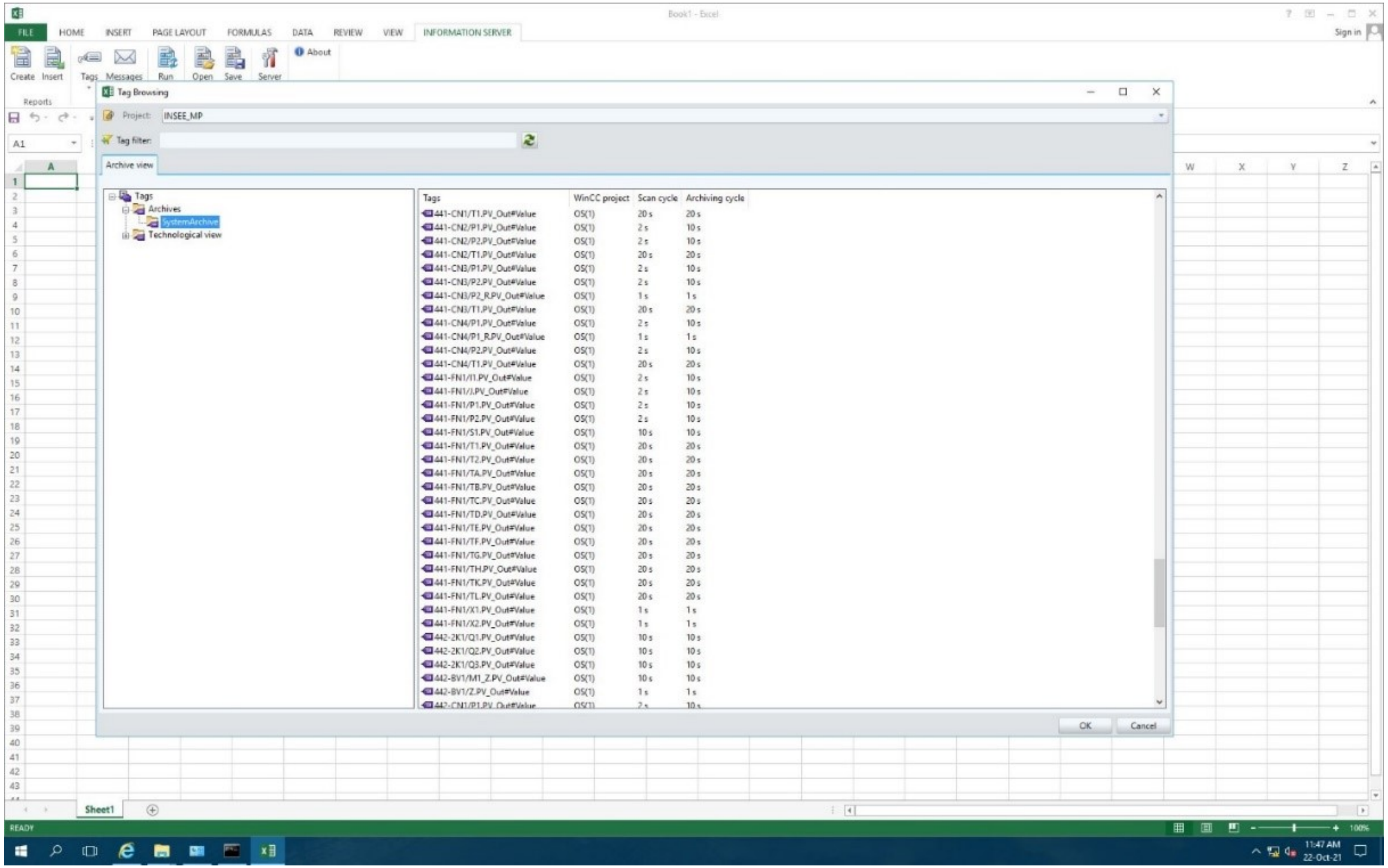


Figure 3.3: Existing Process Tags of MIS & SCADA System

The table 3.3.1 is defined the sensors and equipment that are used to collect data from RKS.

Table 3.3: Sensors and Equipment Used to Collect Data

Kiln Process Parameters	**Sensors and Equipment**
Cyclone Temperature	Thermocouple/ Pt100
Cyclone Pressure	Gauge pressure sensor
Preheater O2, CO, NOx	IR gas analyzers, Electrochemical sensors
Kiln Rotational Speed	Taco meters
Feed rate, Fuel rate, HFO rate, AF rate	Flow meters
Kiln Ampere	CTs

It is needed to configure new process tags of plant MIS to collect sensor data in every 10 seconds intervals during period of January 24, 2021 to April 24, 2021. Following figure 3.4 and figure 3.5 shows the MIS configuration for data collection.

Data records are saved as CSV files for each process parameters and the total number of records are 516,000. To prepare a single dataset, all the data sheets are aggregated and merged to represent all attribute data in one dataset over a given period of time as figure 3.6

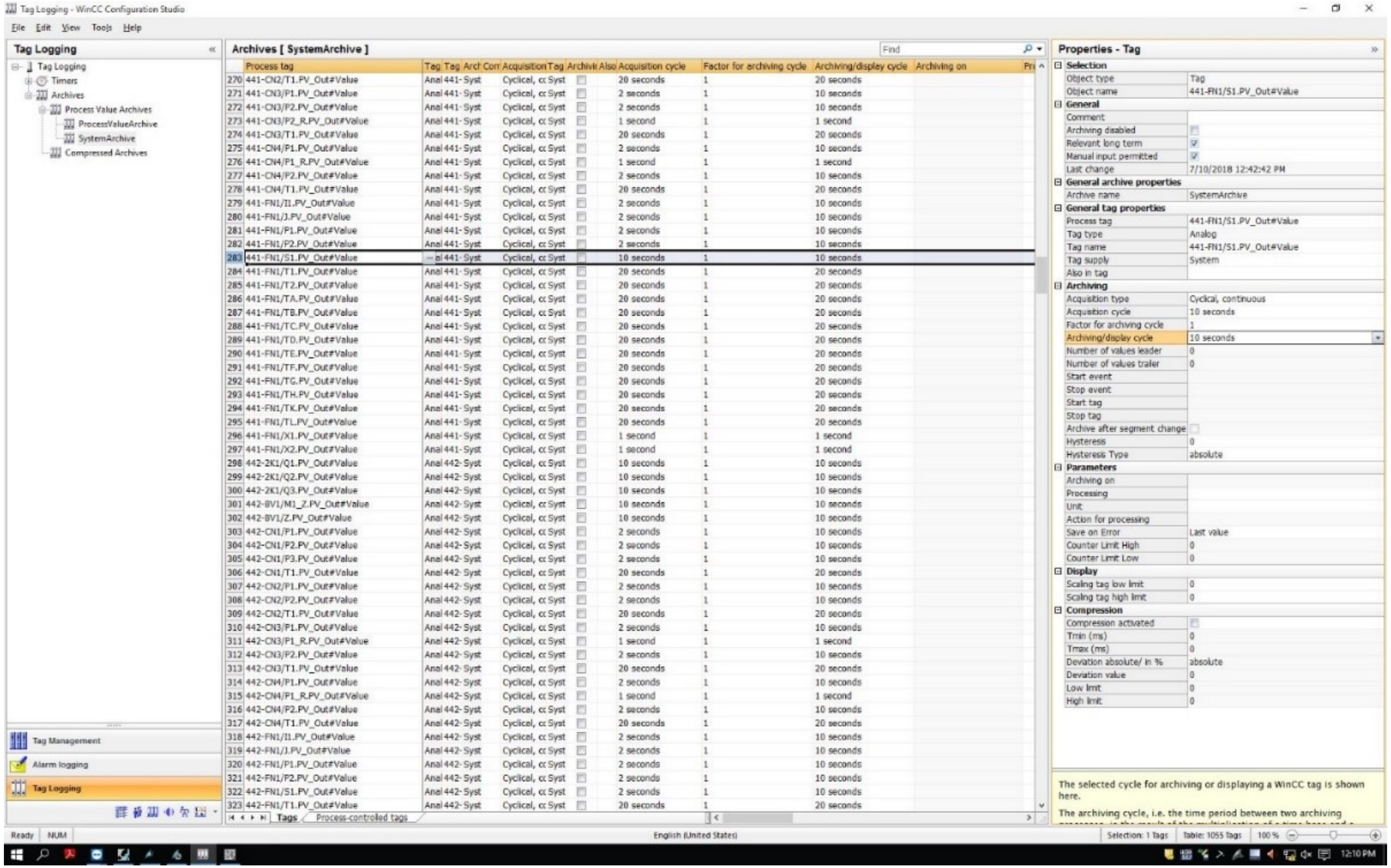


Figure 3.4: Tag Creation for 10s Interval Data Collection

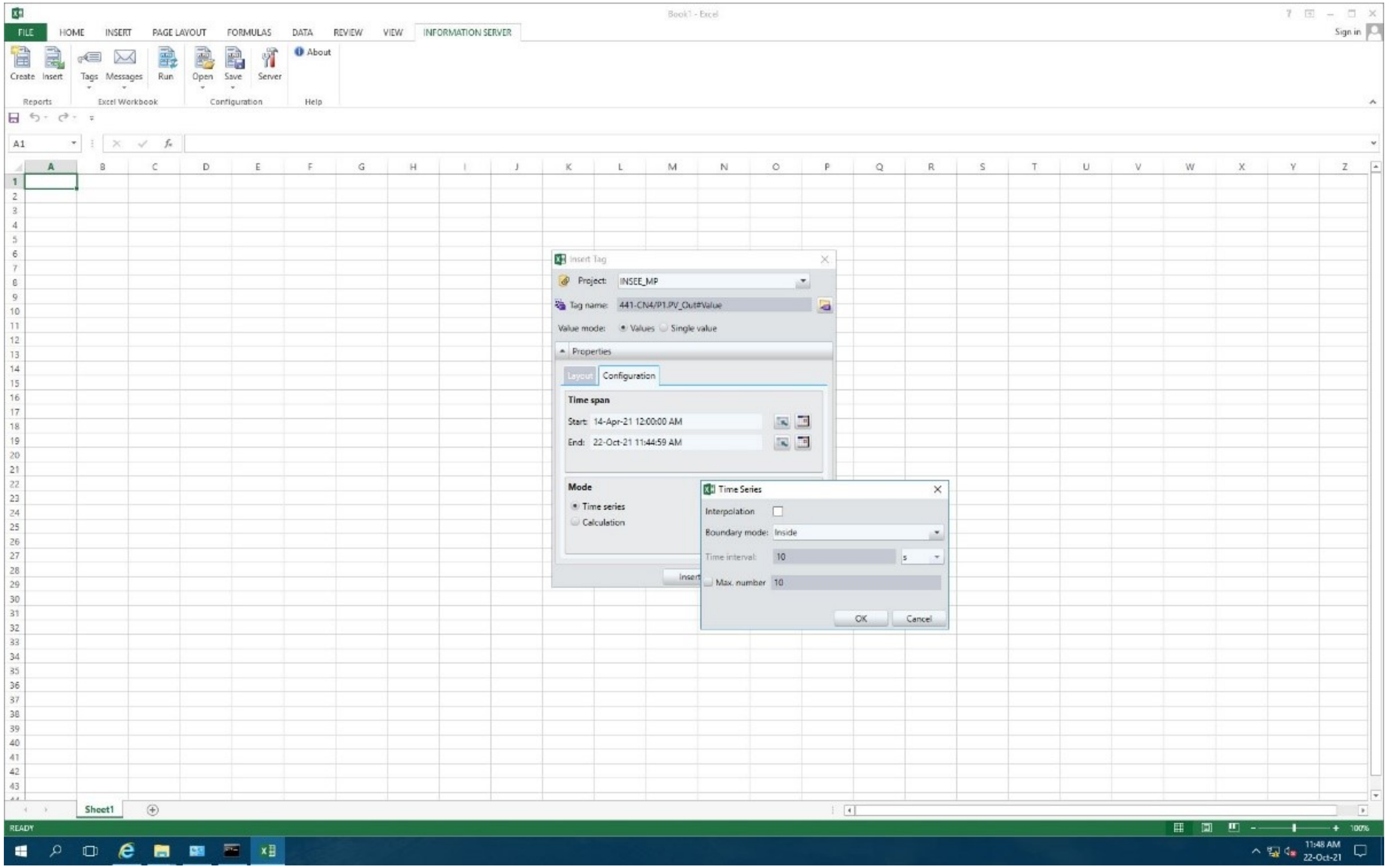
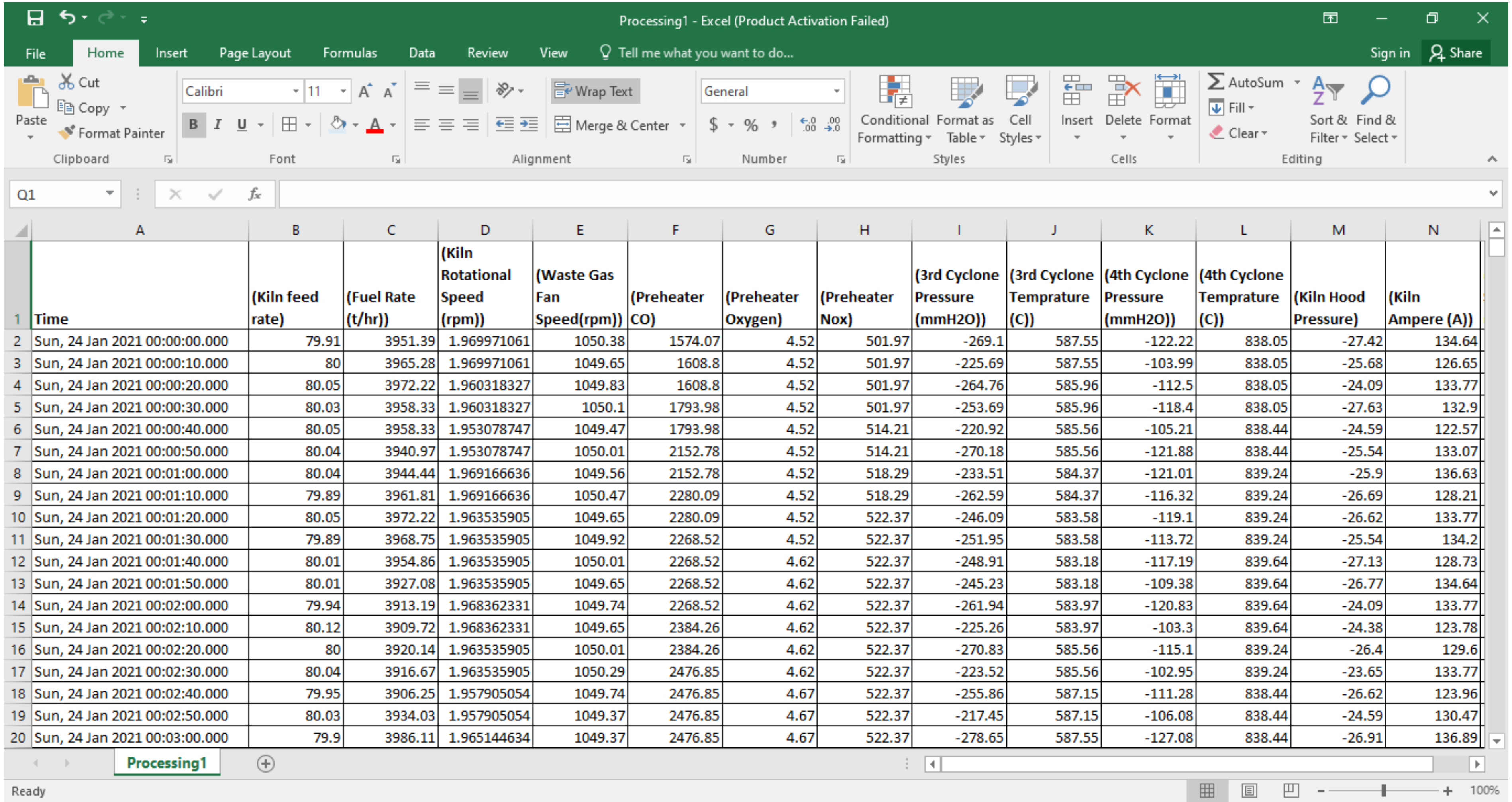


Figure 3.5: Tags Assigning to Excel Sheet to Data Archiving



	Time	(Kiln feed rate)	(Fuel Rate (t/hr))	(Kiln Rotational Speed (rpm))	(Waste Gas Fan Speed(rpm))	(Preheater CO)	(Preheater Oxygen)	(Preheater Nox)	(3rd Cyclone Pressure (mmH2O))	(3rd Cyclone Temprature (C))	(4th Cyclone Pressure (mmH2O))	(4th Cyclone Temprature (C))	(Kiln Hood Pressure)	(Kiln Ampere (A))
2	Sun, 24 Jan 2021 00:00:00.000	79.91	3951.39	1.969971061	1050.38	1574.07	4.52	501.97	-269.1	587.55	-122.22	838.05	-27.42	134.64
3	Sun, 24 Jan 2021 00:00:10.000	80	3965.28	1.969971061	1049.65	1608.8	4.52	501.97	-225.69	587.55	-103.99	838.05	-25.68	126.65
4	Sun, 24 Jan 2021 00:00:20.000	80.05	3972.22	1.960318327	1049.83	1608.8	4.52	501.97	-264.76	585.96	-112.5	838.05	-24.09	133.77
5	Sun, 24 Jan 2021 00:00:30.000	80.03	3958.33	1.960318327	1050.1	1793.98	4.52	501.97	-253.69	585.96	-118.4	838.05	-27.63	132.9
6	Sun, 24 Jan 2021 00:00:40.000	80.05	3958.33	1.953078747	1049.47	1793.98	4.52	514.21	-220.92	585.56	-105.21	838.44	-24.59	122.57
7	Sun, 24 Jan 2021 00:00:50.000	80.04	3940.97	1.953078747	1050.01	2152.78	4.52	514.21	-270.18	585.56	-121.88	838.44	-25.54	133.07
8	Sun, 24 Jan 2021 00:01:00.000	80.04	3944.44	1.969166636	1049.56	2152.78	4.52	518.29	-233.51	584.37	-121.01	839.24	-25.9	136.63
9	Sun, 24 Jan 2021 00:01:10.000	79.89	3961.81	1.969166636	1050.47	2280.09	4.52	518.29	-262.59	584.37	-116.32	839.24	-26.69	128.21
10	Sun, 24 Jan 2021 00:01:20.000	80.05	3972.22	1.963535905	1049.65	2280.09	4.52	522.37	-246.09	583.58	-119.1	839.24	-26.62	133.77
11	Sun, 24 Jan 2021 00:01:30.000	79.89	3968.75	1.963535905	1049.92	2268.52	4.52	522.37	-251.95	583.58	-113.72	839.24	-25.54	134.2
12	Sun, 24 Jan 2021 00:01:40.000	80.01	3954.86	1.963535905	1050.01	2268.52	4.62	522.37	-248.91	583.18	-117.19	839.64	-27.13	128.73
13	Sun, 24 Jan 2021 00:01:50.000	80.01	3927.08	1.963535905	1049.65	2268.52	4.62	522.37	-245.23	583.18	-109.38	839.64	-26.77	134.64
14	Sun, 24 Jan 2021 00:02:00.000	79.94	3913.19	1.968362331	1049.74	2268.52	4.62	522.37	-261.94	583.97	-120.83	839.64	-24.09	133.77
15	Sun, 24 Jan 2021 00:02:10.000	80.12	3909.72	1.968362331	1049.65	2384.26	4.62	522.37	-225.26	583.97	-103.3	839.64	-24.38	123.78
16	Sun, 24 Jan 2021 00:02:20.000	80	3920.14	1.963535905	1050.01	2384.26	4.62	522.37	-270.83	585.56	-115.1	839.24	-26.4	129.6
17	Sun, 24 Jan 2021 00:02:30.000	80.04	3916.67	1.963535905	1050.29	2476.85	4.62	522.37	-223.52	585.56	-102.95	839.24	-23.65	133.77
18	Sun, 24 Jan 2021 00:02:40.000	79.95	3906.25	1.957905054	1049.74	2476.85	4.67	522.37	-255.86	587.15	-111.28	838.44	-26.62	123.96
19	Sun, 24 Jan 2021 00:02:50.000	80.03	3934.03	1.957905054	1049.37	2476.85	4.67	522.37	-217.45	587.15	-106.08	838.44	-24.59	130.47
20	Sun, 24 Jan 2021 00:03:00.000	79.9	3986.11	1.965144634	1049.37	2476.85	4.67	522.37	-278.65	587.55	-127.08	838.44	-26.91	136.89

Figure 3.6: Attribute Data Merged in One Dataset

3.3 Data Analyzing

Collected dataset is analyzed in order to ensure the kiln operations that carried out between time periods (24th January 2021 - 24th April 2021) are performed under kiln stable condition.

The table 3.4 illustrates stoppages details of RKS during data collection period (24th January 2021 – 24th April 2021). And figure 3.7 shows the daily stoppage durations and daily production rates of the RKS during the data collection period. According to the table 3.4, only 9 number of RKS stoppages can be observed within the data collection period.

Table 3.4: Kiln Stoppage Report during the Data Collection Period

DATE	Kiln#1 Running Hours	Daily Production (tons)	Stoppages			
			Start Time	End Time	Time duration	Reason
2-Feb	23.17	995	8:32	8:50	0:18	4th cyclone blockage
3-Feb	24	1,130	8:50	9:12	0:22	FK pump defect
4-Feb	24	1,125	13:13	13:16	0:03	Power failure
7-Feb	23	973	21:15	22:15	1:00	2nd cyclone blockage
2-Apr	23.31	1,140	2:12	2:41	0:29	Power failure
4-Apr	23.36	1,125	18:39	19:03	0:24	Power failure
5-Apr	23.26	1,114	16:04	16:38	0:34	Power failure
14-Apr	23.29	1,067	15:50	16:21	0:31	Power failure
22-Apr	23.38	1,067	14:32	14:54	0:22	Material not extract from both silos

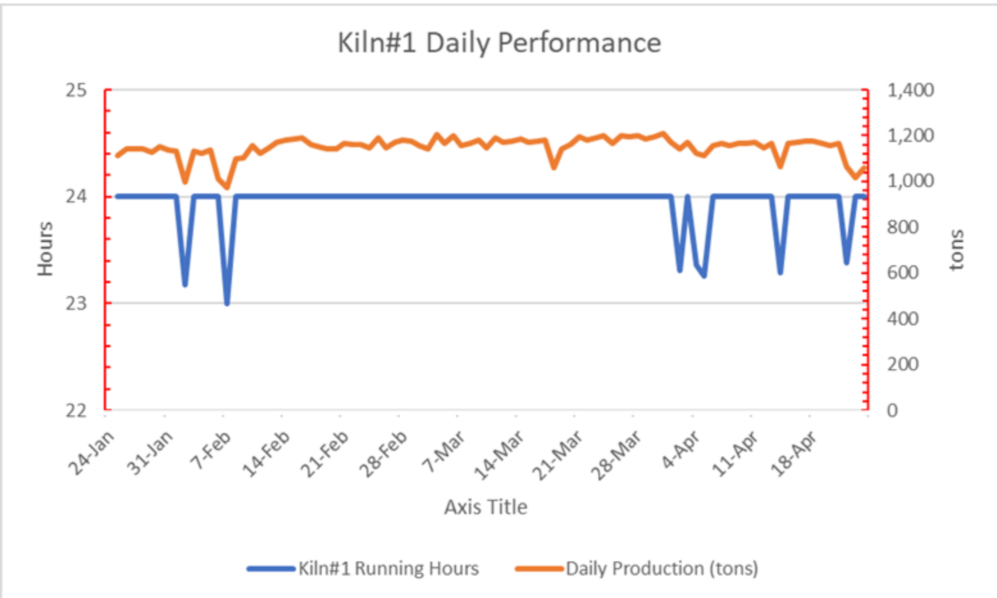


Figure 3.7: Kiln Stoppages during Data Collection Period

3.4 Data Pre-processing

The raw data collected is transformed into a form that is suitable for modelling. Typical data processing steps are performed [21]

On this regression based predictive modeling research study, raw data cannot apply to the model directly. This is because;

- Machine learning algorithms impose requirements on the data
- Statistical noise and errors in the data can be affected to the model
- Complex nonlinear relationships are implemented using the data

Accordingly, raw data must be pre-processed before it fit to the machine learning model and evaluate the model [22].

Following sub tasks are executed during the data preparation.

3.4.1 Data Cleaning

Under the data cleaning, outlier removal or fixing of missing data is carried out. Data which are taken at kiln stoppages, data with outer ranges and data taken at unstable process conditions are removed to extract the dataset with good performance of kiln operation. Also, some values are missed in some records and KNN algorithm which uses 'feature similarity' to predict missing data is used to predict and fill them. This means that a value is assigned based on how close the missing point is to the other points in the dataset.

KNNImputer function from the impute module of the sklearn with Euclidean distance matrix is used to impute missing values in the observations by finding the nearest neighbors. After performed data cleaning, number of data is 485,000.

KNN value is calculated by equation (3.1),

$$\mathrm{d_{xy}} = \sqrt{\text{weight} * \text{squared distance from present coordinates}} \quad (3.1)$$

Where,

$$weight = \frac{\text{Total number of coordinates}}{\text{Number of present coordinates}}$$

3.4.2 Data Scaling

The preprocessed dataset contains attributes with a mixture of scales for various quantities.

Ex :

- Preheater Oxygen (4 – 5 %)
- Preheater Nox (0 – 1000 ppm)
- 3rd Cyclone Pressure (180 – 250 mmH_2O)
- Fuel Rate (3000 - 6000 kg/h)

Most of the machine learning algorithms prefer data attributes to have the same scale, such as between 0 and 1 for a given feature. This can be achieved by normalizing or standardizing the attribute values. Changes in feature scales of feature variables can increase the difficulties of implementing the model [23].

As an example, large input values (e.g. Fuel Rate) can causes that learns large weight values in the model. According to that, scaling the input and output variables is an essential task and it is a critical step in data preparation.

MinMaxScaler() method from scikit's preprocessing library is used to rescale variable values in to range [0 - 1].

Equation (3.2) is used to perform data scaling.

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (3.2)$$

Before and after applying the scaling function to the three features, is shown in figure 3.8

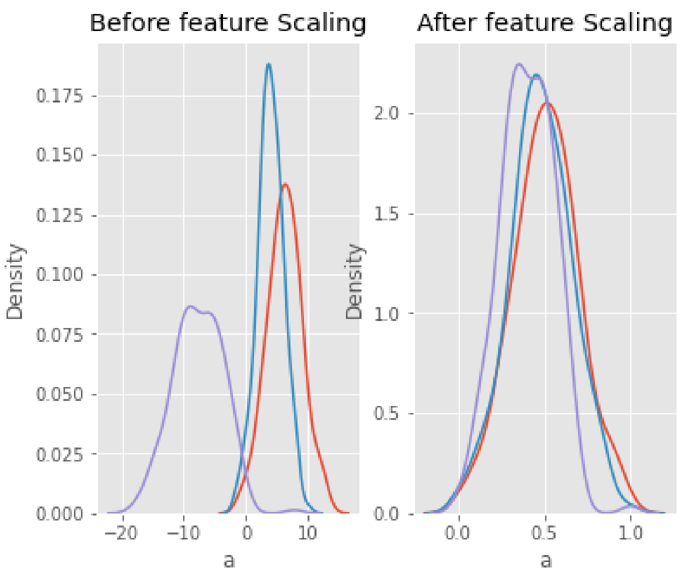


Figure 3.8: Before and After the Data Scaling

3.4.3 Dataset Finalizing

The normalized dataset is split into training and validation data using split() function in skleran

- Train set: 80% of total data
- Test set: 20 % of total data

3.5 Algorithm Selection and Model Design

3.5.1 Multivariate Regression

Multivariate Regression is a supervised machine learning algorithm which is an extension of multiple regression with one dependent variable and multiple independent variables. It is included analysis of multiple data variables. Since the research study has multiple independent variables such as fuel rate, kiln rotational speed, grate drive speed which is get influenced by other variables such as cyclone temperature and pressure for a single prediction.

Therefore, in this research study, three multivariate regression models are required to implement prediction of fuel rate, waste gas fan speed and kiln rotational speed simultaneously [13].

3.5.2 DNN neural network for regression

The purpose of using Deep Neural Networks for Regression rather than Linear Regression is that the linear regression can only learn the linear relationship between the features and target, and therefore complex non-linear relationships cannot be learned. In order to learn the complex nonlinear relationship between features and targets, several other techniques must be considered. One of those techniques is to use Artificial Neural Networks which have the ability to learn the complex relationship between the features and target due to the presence of activation function in each layer.

The ReLU activation function is proposed to implement the DNN model for the study which has gained popularity in the deep learning domain [12]. ReLU stands for Rectified Linear Unit.

The advantages of using ReLU activation over the other activation function are as follows [2]

- ReLU function is more efficient and computational compared to other functions since it only uses a definite number of neurons compared to the other activation functions.

- ReLU function can accelerate the convergence of gradient descent towards the global minimum of the loss function because it has linear, non-saturating properties.

Adagrad is selected as the optimization algorithm for model train. It eliminates the requirement of manual tune for the learning rate [11].

3.5.3 Estimator API in TensorFlow for DNN Regression

The Estimators API in tensor flow comes with a Deep Neural Network classifier and regressor estimator that provide train, evaluation, prediction, and export capabilities. It can be used for continuous value prediction as the set of numeric values are considered as inputs and next numeric value will be predicted accordingly.

The way the Estimators API in TensorFlow works is using an input_fn to read data that returns inputs and labels instead of x and y. The inputs are dictionary of all the inputs (name-of-input to tensor) and the labels are tensors.

As this research is aimed to predict three critical parameters of RKS independently, three DNN regression estimators which are built with RELU activation function and Adagrad optimizer are used to design and implement the model. Figure 3.9 depicts the structure of a DNN model that works inside DNNRegressor estimator comprising a single input layer including 19 inputs and an output. The hidden layer is designed so that all l layers contain m nodes.

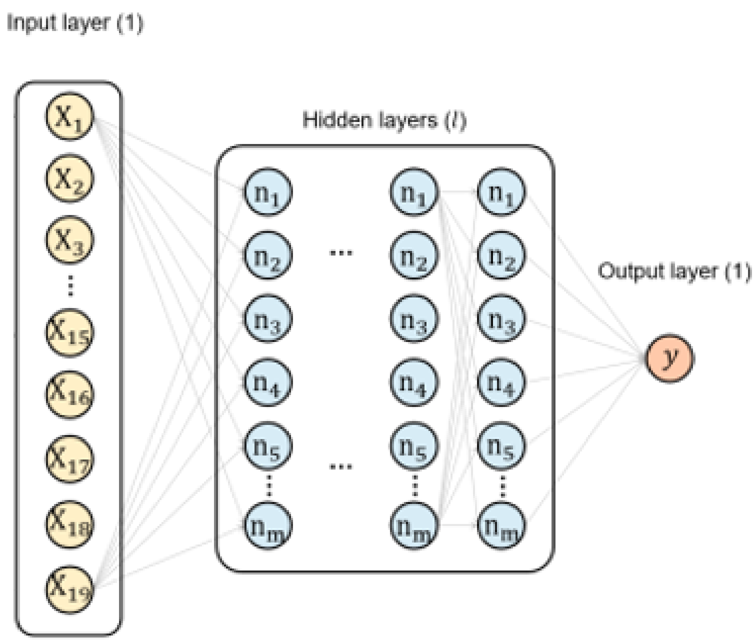


Figure 3.9: Structure of a DNN Model Inside DNNRegressor Estimator

Figure 3.10 depicts the design of the proposed model for the predictions of fuel rate, kiln rotational speed and waste gas fan speed.

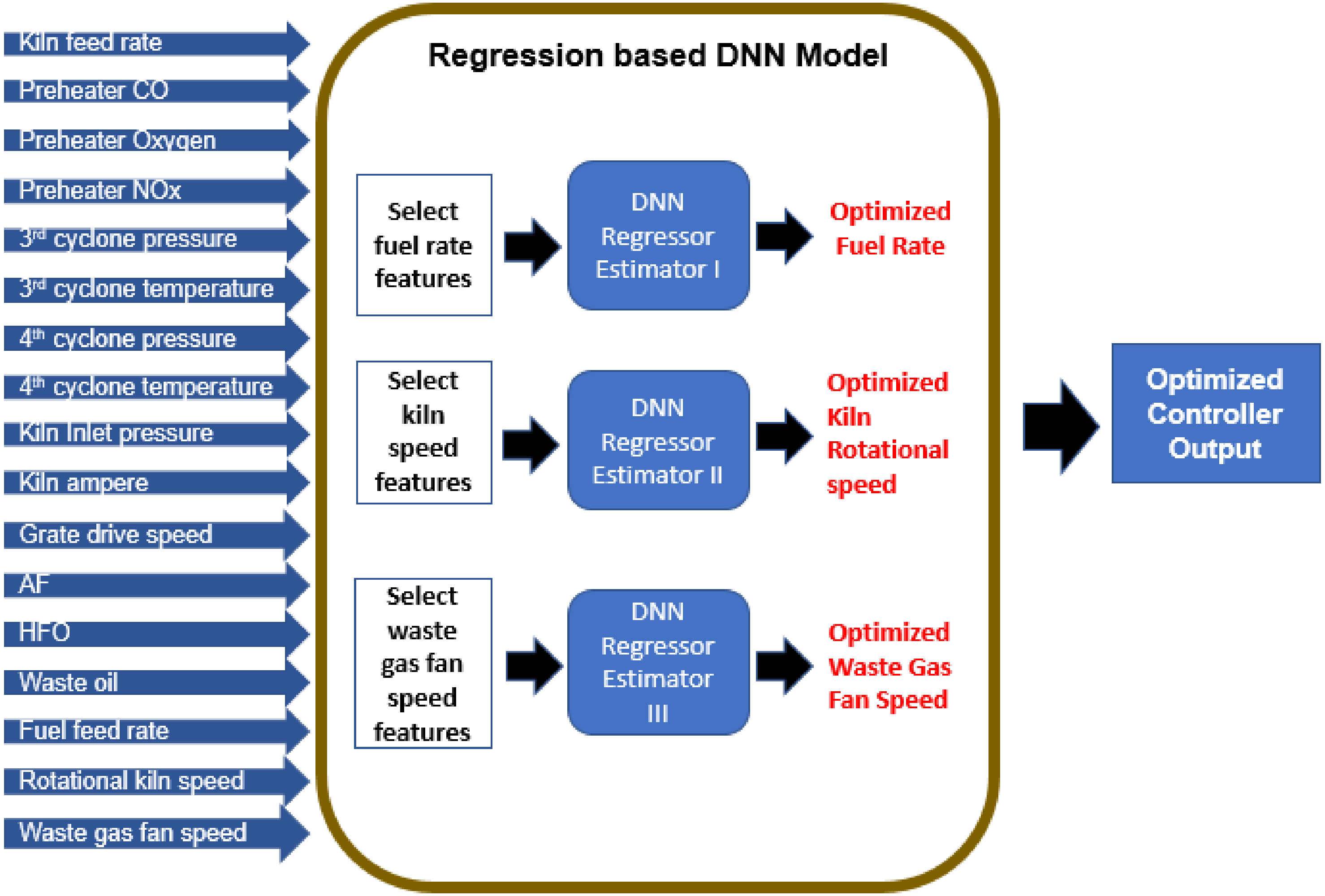


Figure 3.10: Design of the Proposed Model

3.6 Model Implementation

The goal of this research is to create a model to predict fuel rate, kiln rotation speed, waste gas fan speed simultaneously. Architecture of the model implementation is illustrated in Fig 3.11

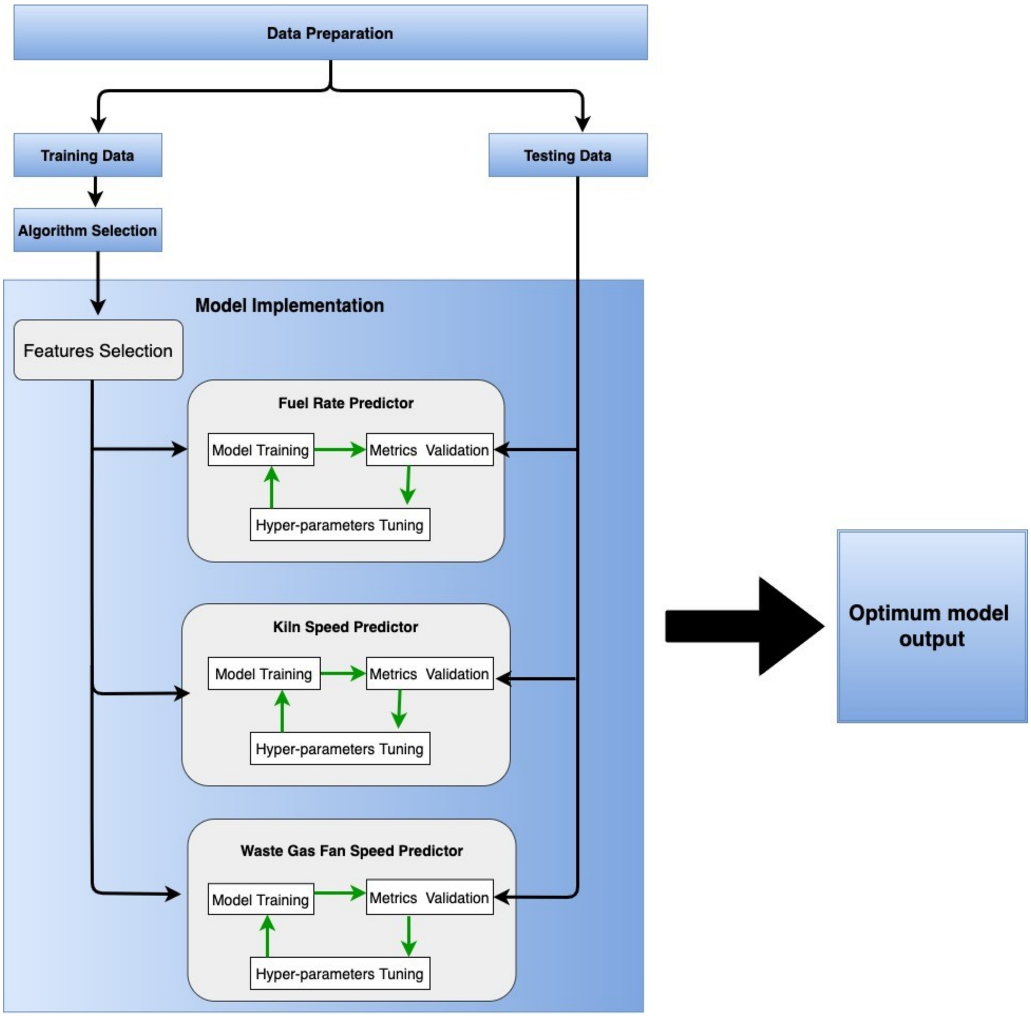


Figure 3.11: Implementation Architecture of the Overall Model

The model training, model evaluation and model tuning are carried out repeatedly until find the optimum estimators for each three predictions.

Model Training

The training dataset which is extracted from the dataset is inserted to each three predictors (Fuel Rate, Kiln Rotational Speed and Waste Gas Fan Speed) with relevant features. Each of predictors learn the RKS behavioral patterns independently by training with given hyperparameters such as batch size, train steps, epochs, number of hidden layers and their hidden units.

Model Evaluation

Then, the model evaluation on for different hyper-parameters which helps to optimize the model performance, fine-tune the model for a better result is carried out stepwise and validated the results for each three estimators.

The sklearn.metrics module is used to obtain the results for R-squared, Mean Squared Error and Mean Absolute Error. The results are noted for final evaluation.

This is done multiple times by tuning the hyper parameters of the neural network in order to pick the most accurate regression function.

Hyperparameter Tuning

Different sets of hyper-parameters are required to predict accurately by three models. However, a large number of hyperparameters make it difficult for users to decide what to select. It cannot exactly say about, how many layers, neurons are appropriate, which optimizer is best for all datasets. The tuning is important to find the best sets of hyper-parameters to build each three models from the dataset. Following ways are used to tune a neural network until obtaining the best model.

- Hyper parameters adjustment: Number of neurons, batch size, steps and epochs
- Number of layers

3.6.1 Prediction Model

Once all the features are entered to the model, each predictor select its' own features and pass them to relevant estimator and predict the control variables for RKS according to the figure 3.12

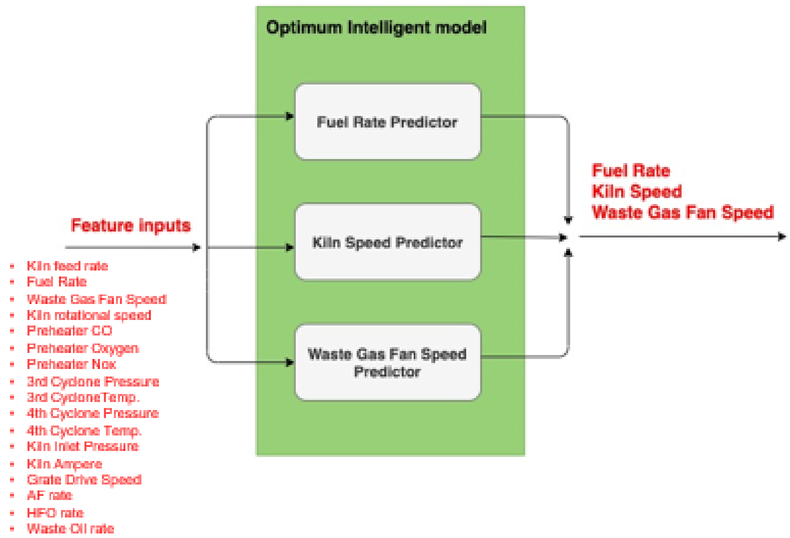


Figure 3.12: Real time Prediction of Three Control Variables

Equations (3.3), (3.4) and (3.5) show the predictor model equations for fuel rate, kiln speed and waste gas fan speed.

Fuel Rate Predictor Model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + .\dots + \beta_{15} x_{15} \qquad (3.3)$$

$x_{1,} x_2, x_3, \dots, x_{15}$ are Kiln Rotational Speed, Waste Gas Fan Speed, Preheater CO, Preheater Oxygen, Preheater Nox, 3rd Cyclone Pressure, 3rd Cyclone Temp, 4th Cyclone Pressure, 4th Cyclone Temp, Kiln Hood Pressure, Kiln Ampere, Grate Drive Speed, AF rate, HFO rate, Waste Oil rate.

y is the predicted value for fuel rate.

Kiln Rotational Speed Predictor Model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + .\dots + \beta_{15} x_{15} \qquad (3.4)$$

$x_{1,} x_2, x_3, \dots, x_{15}$ are Fuel rate, Waste Gas Fan Speed, Preheater CO, Preheater Oxygen, Preheater Nox, 3rd Cyclone Pressure, 3rd Cyclone Temp, 4th Cyclone Pressure, 4th Cyclone Temp, Kiln Hood Pressure, Kiln Ampere, Grate Drive Speed, AF rate, HFO rate, Waste Oil rate

y is the predicted value for kiln rotational speed.

Waste Gas Fan Speed Predictor Model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + .\dots + \beta_{15} x_{15} \qquad (3.5)$$

$x_{1,} x_2, x_3, \dots, x_{15}$ are Fuel rate, Kiln Rotational Speed, Preheater CO, Preheater Oxygen, Preheater Nox, 3rd Cyclone Pressure, 3rd Cyclone Temp, 4th Cyclone Pressure, 4th Cyclone Temp, Kiln Hood Pressure, Kiln Ampere, Grate Drive Speed, AF rate, HFO rate, Waste Oil rate

y is the predicted value for waste gas fan speed.

3.7 Model Accuracy Calculation

Usually mean absolute error (MAE), mean squared error (MSE) and R squared error (R2) are used to evaluate the accuracy of a DNN regression model.

3.7.1 Mean Absolute Error (MAE)

MAE calculates the absolute difference between actual and predicted values. (Equation (3.6))

$$\mathrm{MAE} = \frac{1}{\mathrm{N}} \sum |\, \mathrm{Y} - \acute{\mathrm{Y}}| \qquad (3.6)$$

Advantages of MAE

- The unit of the MAE output variable is same.
- MAE is mostly robust to outliers.

Disadvantages of MAE

- MAE is not directly differentiable. So that, it is required some optimizers to convert as differentiable.

3.7.2 Mean Squared Error (MSE)

MSE is often used and is slightly different from the mean absolute error. It states the squared difference between actual and predicted value. MSE is calculated using equation 3.7

$$MSE = \frac{1}{\mathrm{N}} \sum (\, \mathrm{Y} - \acute{\mathrm{Y}})^2 \qquad (3.7)$$

Advantages of MSE

- MSE can be differentiated so it can be easily used as a loss function.

Disadvantages of MSE

- Unit of the MSE is square unit of output.
- MSE is not robust to outliers. It highlights the outliers most and the calculated MSE is large.

3.7.3 Root Mean Squared Error (RMSE)

RMSE is the simple square root of mean squared error, calculated using equation 3.8

$$RMSE = \sqrt{\frac{1}{\mathrm{N}} \sum (\, \mathrm{Y} - \acute{\mathrm{Y}})^2} \qquad (3.8)$$

Advantages of RMSE

- Unit of the RMSE is same as the output value, making it easier to define the loss.

Disadvantages of RMSE

- Compared to MAE, RMSE is not much robust to outliers.

3.7.4 R Squared (R2)

R2 score revels the performance of the model. This does not show the loss in an absolute sense but how many wells the model is performed. Furthermore, MAE and MSE depend on the context and R2 is independent of the score context. Equation 3.9 shows the calculation of R2.

$$R^2 = 1 - \frac{\mathrm{SSR}}{\mathrm{SSM}} \qquad (3.9)$$

SSR – Squared sum error of regression line

SSM – Squared sum error of mean line

4. RESULTS AND VALIDATION

In order to demonstrate the relevance and effectiveness of the proposed model hyperparameters were adjusted and tested the model until obtain a minimum error. Accuracy of the model was determined by analyzing R_Squared Error, Mean Absolute Error and Root Mean Squared Error.

RKS has been operated for 2 hours (7th of November 2021, at 16.00 to 18.00 hours) to evaluate the real-time performance of the model, using model predicted control variable outputs (fuel rate, kiln rotational speed and waste gas fan speed) and all the process parameters were recorded. This simulation was performed for different feed rates. Also, some standard quality tests; FCaO, LSF and C3S were performed at hourly frequencies.

4.1 Predictor Evaluation Results

4.1.1 Fuel Rate Prediction Results

Hyperparameters were adjusted for training the model until get a minimum error. Best accuracy of R_Sq = 0.92, MAE = 221.56 and RMSE = 255.12 for the trained model has been obtained. Table 4.1 shows the hyperparameter adjustment attempts while training the model and the relevant accuracy calculations. Figure 4.1, 4.2 and 4.3 shows the accuracy results of R2, MAE and RMSE while training the model.

Table 4.1: Hyperparameter Adjustment for Fuel Rate Prediction

No. of Hidden Layers	Hyper Para. Configuration	No. of Hidden Layer Nodes	Batch Size	Epochs	Train Steps	Accuracy Results		
						R_Sq	MAE	RMSE
4	Config. 1	1024,512,256,128	80	10000	40000	0.73	297.64	400.95
	Config. 2	1024,512,256,128	80	10000	60000	0.73	296.93	400.69
	Config. 3	1024,512,256,128	100	10000	60000	0.75	287.53	385.63
	Config. 4	1024,512,256,128	150	10000	60000	0.74	294.44	395.73
	Config. 5	1024,512,256,128	120	10000	80000	0.76	285.51	383.27
5	Config. 6	2048, 1024,512, 256, 128	120	10000	80000	0.78	274.92	363.27
	Config. 7	2048, 1024,512, 256, 128	120	20000	100000	0.79	271.77	358.72
	Config. 8	2048, 1024,512, 256, 128	120	20000	200000	0.78	273.52	360.78
	Config. 9	2048, 1024,512, 256, 128	100	25000	200000	0.79	272.86	359.23
	Config. 10	2048, 1024,512, 256, 128	120	20000	150000	0.79	272.54	359.62
	Config. 11	2048, 1024,512, 256, 128	120	20000	150000	0.79	270.94	356.49
	Config. 12	4096, 1024,512, 256, 128	150	20000	150000	0.89	227.94	276.49
6	Config. 13	4096,2048,1024,512,256,128	120	20000	50000	0.81	241.56	335.12
	Config. 14	4096,2048,1024,512,256,128	120	20000	80000	0.82	236.55	310.25
	Config. 15	4096,2048,1024,512,256,128	130	20000	82000	0.83	233.97	300.46
	Config. 16	4096,2048,1024,512,256,128	140	25000	80000	0.84	231.58	289.46
	Config. 17	4096,2048,1024,512,256,128	180	25000	150000	0.92	221.56	255.12
	Config. 18	4096,2048,1024,512,256,128	180	25000	200000	0.91	224.55	266.25
	Config. 19	4096,2048,1024,512,256,128	180	20000	250000	0.87	238.66	342.64

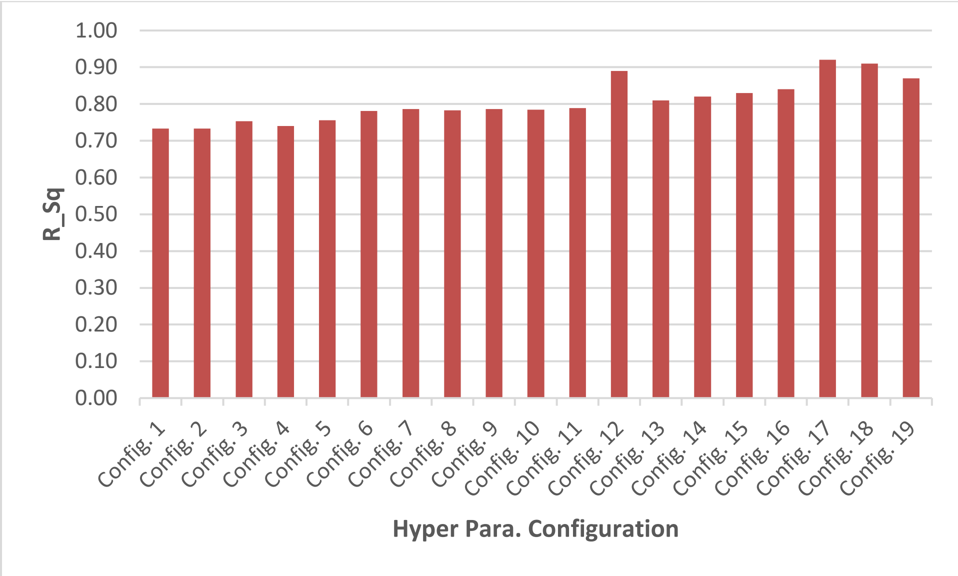


Figure 4.1: R2 Results while Training the Fuel Prediction Model

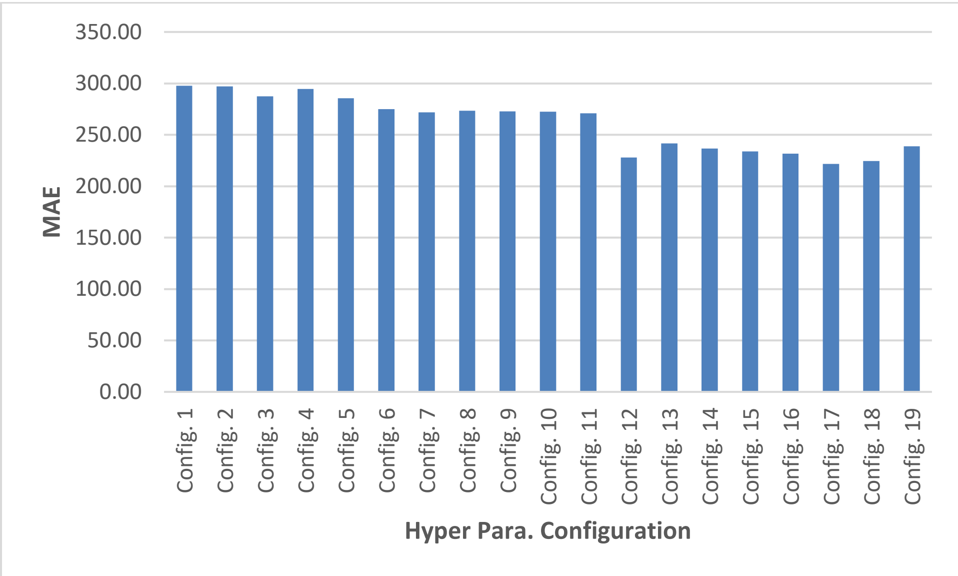


Figure 4.2: MAE Results while Training the Fuel Prediction Model

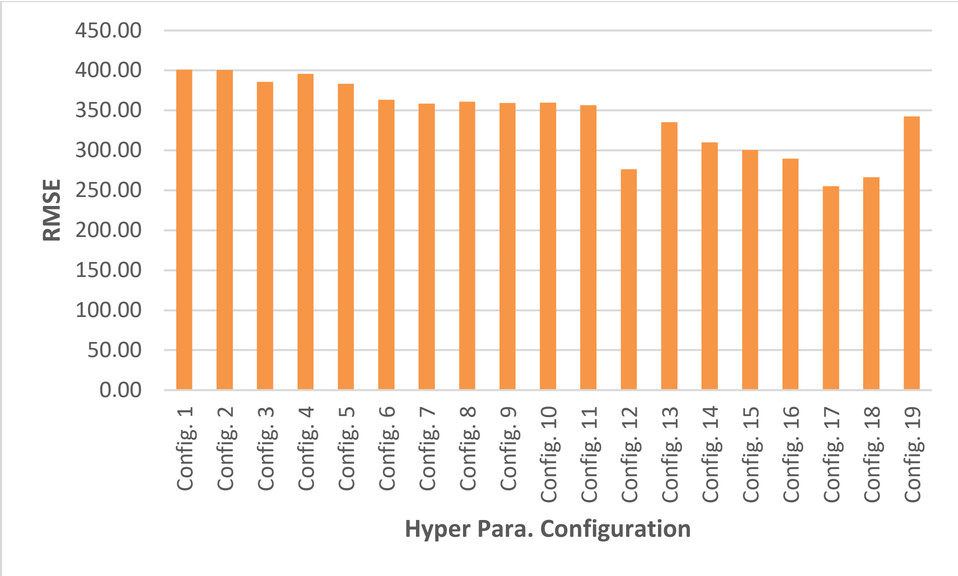


Figure 4.3: RMSE Results while Training the Fuel Prediction Model

According to above results, it is obtained that the highest accuracy of the model training is given by hyperparameter configuration set 17. Actual fuel rate vs predicted fuel rate, according to the hyperparameter configuration set 17 is shown in figure 4.4.

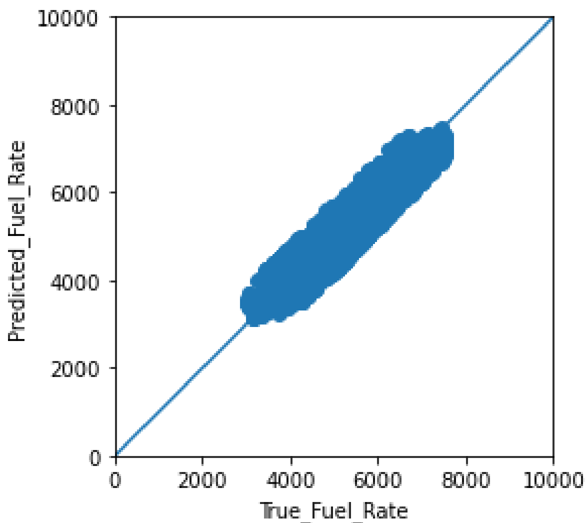


Figure 4.4: Actual Fuel Rate vs Predicted Fuel Rate

4.1.2 Kiln Speed Prediction Results

Hyperparameters were adjusted for training the model until get a minimum error. Best accuracy of R_Sq = 0.81, MAE = 0.05 and RMSE = 0.01 for the trained model has been obtained. Table 4.2 shows the hyperparameter adjustment attempts while training the model and the relevant accuracy calculations. Figure 4.1 show the graph of actual vs predicted kiln rotational speed. Figure 4.5, 4.6 and 4.7 shows the accuracy results of R2, MAE and RMSE while training the model.

Table 4.2: Hyperparameter Adjustment for Kiln Speed Prediction

No. of Hidden Layers	Hyper Para. Configuration	No. of Hidden Layer Nodes	Batch Size	Epochs	Train Steps	Accuracy Results		
						R_Sq	MAE	RMSE
4	Config. 1	1024,512,256,128	20	4000	10000	0.19	0.06	0.01
	Config. 2	1024,512,256,128	50	5000	80000	0.21	0.06	0.01
	Config. 3	1024,512,256,128	80	5000	80000	0.25	0.06	0.01
5	Config. 4	2048, 1024,512, 256, 128	120	5000	50000	0.50	0.07	0.01
	Config. 5	2048,1024,512,256,128	150	5000	80000	0.54	0.06	0.01
6	Config. 6	4096,2048,1024,512,256,128	150	5000	100000	0.89	0.05	0.01
	Config. 7	4096,2048,1024,512,256,128	50	5000	100000	0.73	0.06	0.01

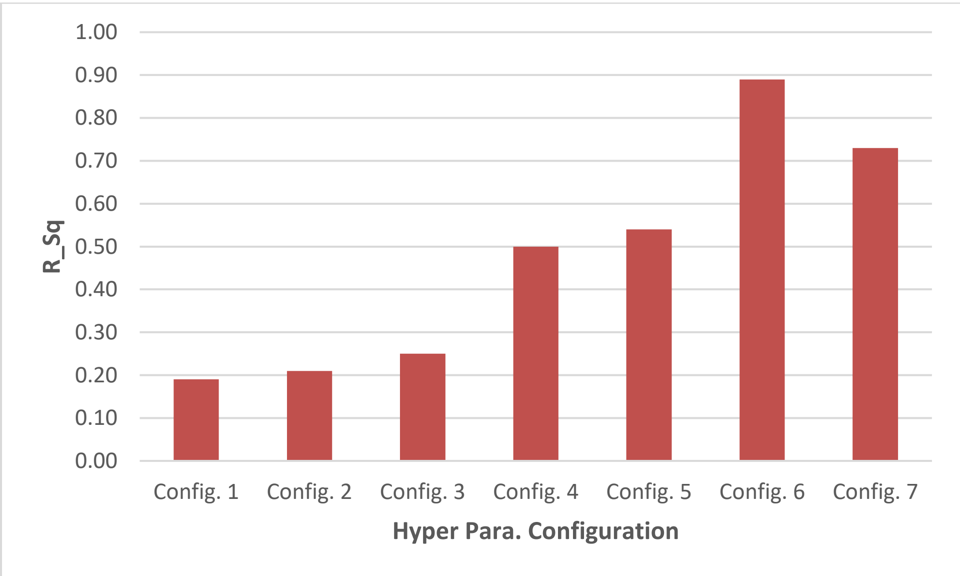


Figure 4.5: R2 Results while Training the Kiln Speed Prediction Model

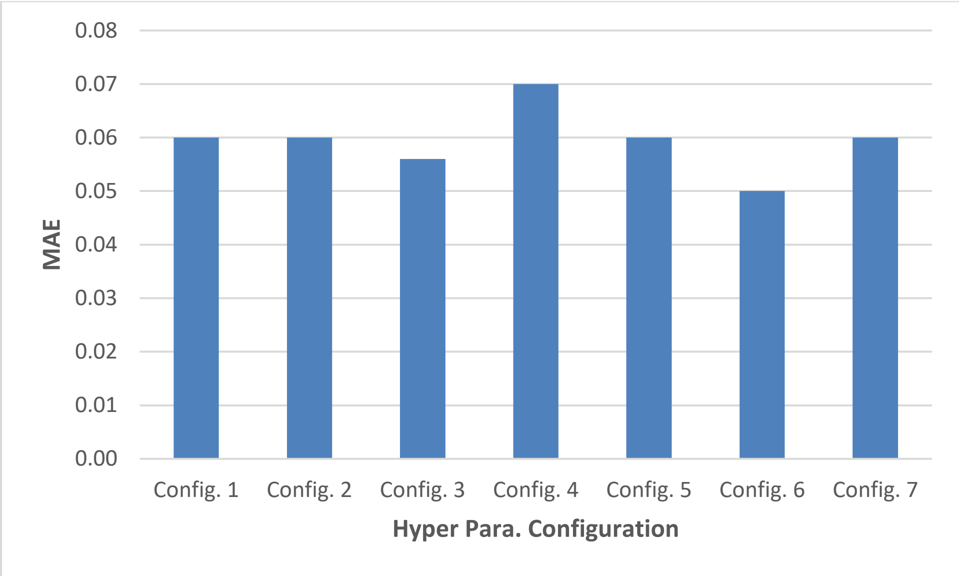


Figure 4.6: MAE Results while Training the Kiln Speed Prediction Model

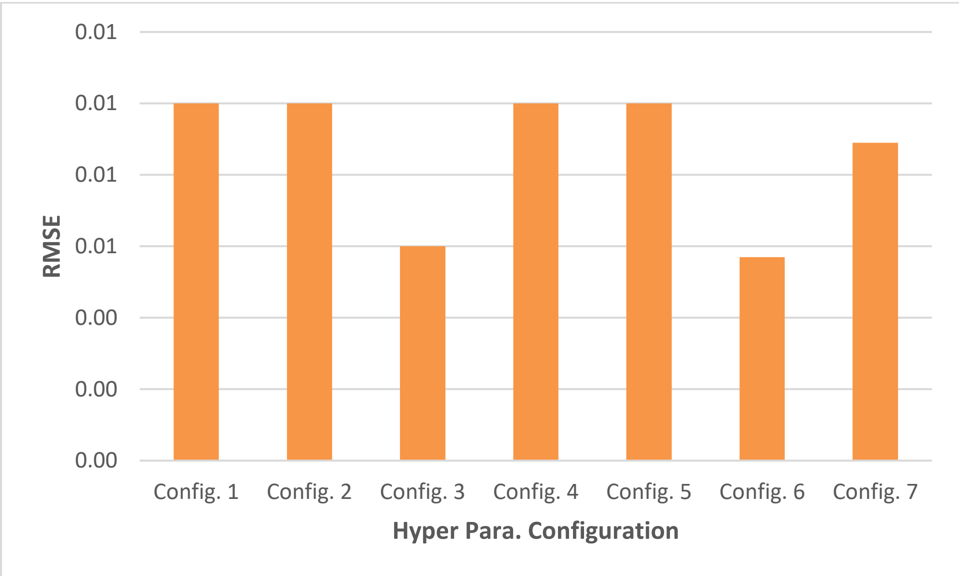


Figure 4.7: MAE Results while Training the Kiln Speed Prediction Model

According to above results, it is obtained that the highest accuracy of the model training is given by hyperparameter configuration set 6. Actual kiln rotational speed vs predicted kiln rotational speed, according to the hyperparameter configuration set 6 is shown in figure 4.8.

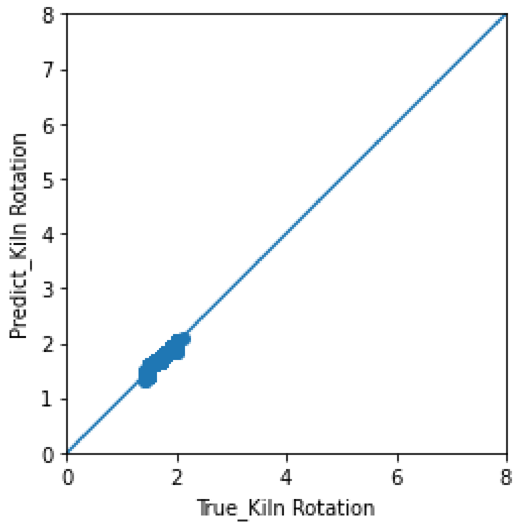


Figure 4.8: Actual Kiln Rotational Speed vs Predicted Kiln Rotational Speed

4.1.3 Waste Gas Fan Speed Prediction Results

Hyperparameters were adjusted for training the model until get a minimum error. Best accuracy of R_Sq = 0.85, MAE = 5.68 and RMSE = 8.46 for the trained model has been obtained. Table 4.2 shows the hyperparameter adjustment attempts while training the model and the relevant accuracy calculations. Figure 4.9, 4.10 and 4.11 shows the accuracy results of R2, MAE and RMSE while training the model.

Table 4.3: Hyperparameter Adjustment for Waste Gas Fan Speed Prediction

No. of Hidden Layers	Hyper Para. Configuration	No. of Hidden Layer Nodes	Batch Size	Epochs	Train Steps	Accuracy Results		
						R_Sq	MAE	RMSE
4	Config. 1	1024,512,256,128	120	8000	20000	0.71	11.85	15.25
	Config. 2	1024,512,256,129	150	8000	20000	0.73	11.78	15.15
5	Config. 3	2048,1024,512,256,128	120	5000	80000	0.78	11.34	15.00
	Config. 4	2048,1024,512,256,128	120	10000	80000	0.74	11.73	16.24
	Config. 5	2048,1024,512,256,128	150	5000	80000	0.75	11.74	15.96
	Config. 6	2048,1024,512,256,128	120	5000	90000	0.77	11.42	15.31
6	Config. 7	4096,2048,1024,512,256,128	120	5000	90000	0.79	11.10	14.58
	Config. 8	4096,2048,1024,512,256,128	130	5000	90000	0.81	10.89	13.25
	Config. 9	4096,2048,1024,512,256,128	130	5000	100000	0.79	11.01	13.89
	Config. 10	4096,2048,1024,512,256,128	140	5000	90000	0.83	8.76	11.28
	Config. 11	4096,2048,1024,512,256,128	150	10000	90000	0.85	5.68	8.46
	Config. 12	4096,2048,1024,512,256,128	155	10000	90000	0.88	5.64	8.25
	Config. 13	4096,2048,1024,512,256,128	160	10000	90000	0.82	9.23	12.25
	Config. 14	4096,2048,1024,512,256,128	120	5000	100000	0.78	11.44	14.9
	Config. 15	4096,2048,1024,512,256,128	150	5000	100000	0.77	11.76	15.29

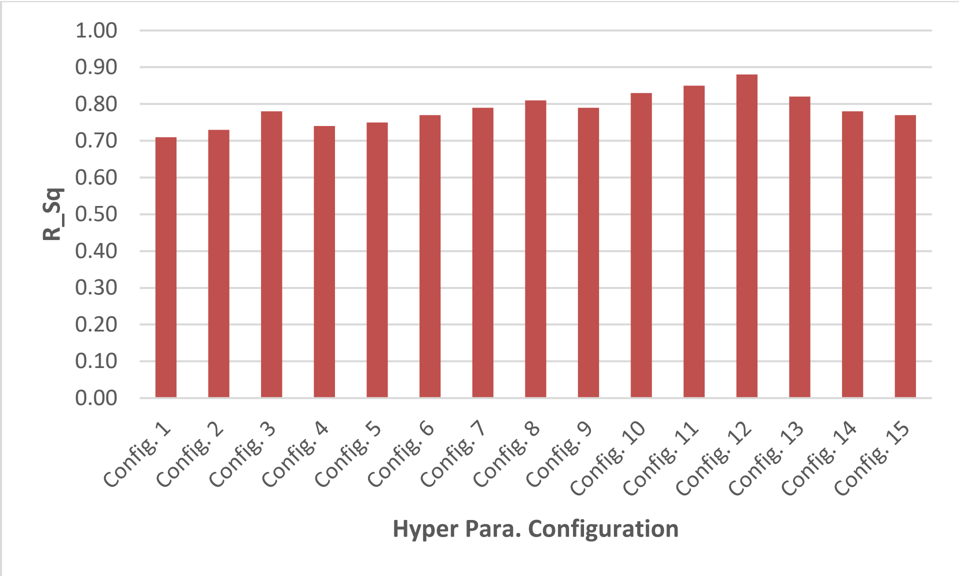


Figure 4.9: R2 Results while Training the Waste Gas Fan Speed Prediction Model

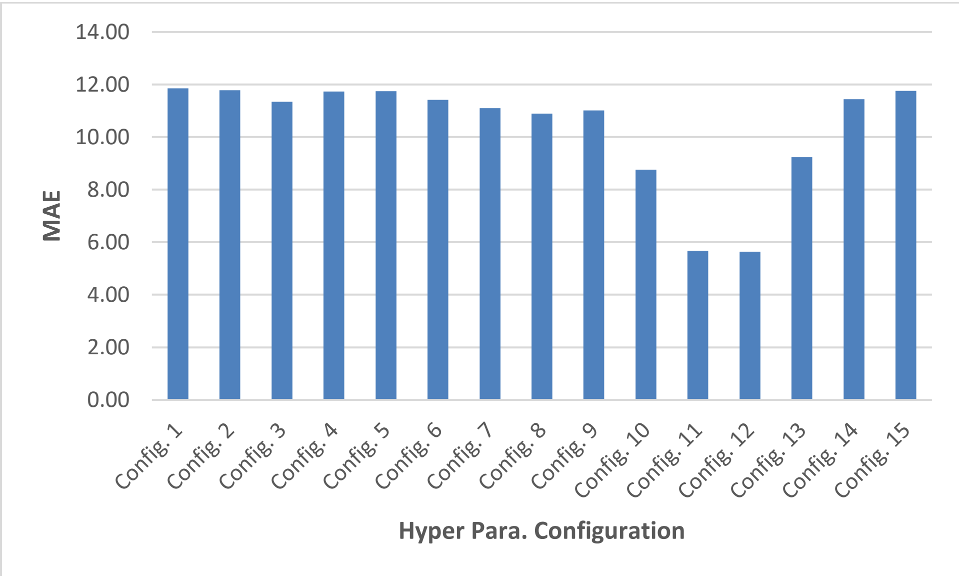


Figure 4.10: MAE Results while Training the Waste Gas Fan Speed Prediction Model

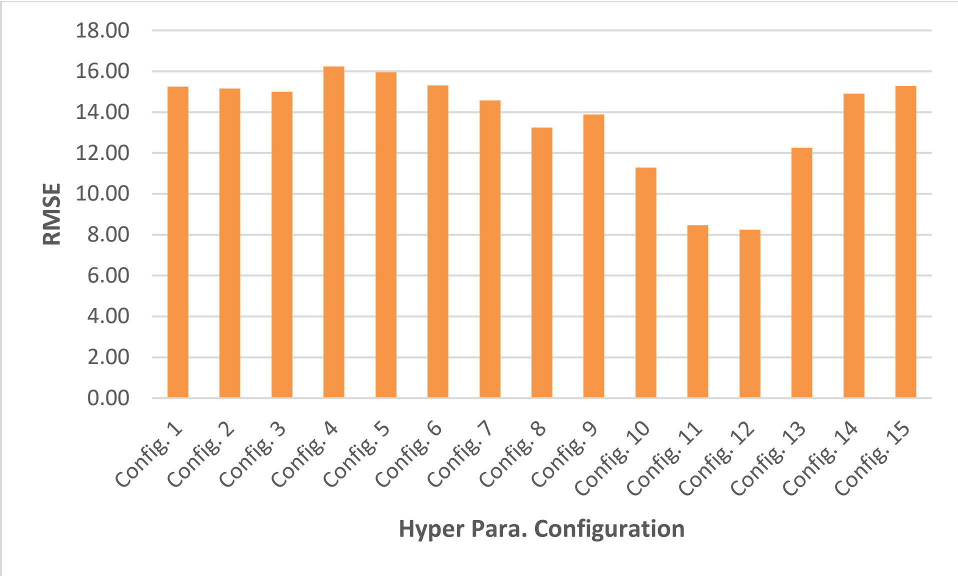


Figure 4.11: RMSE Results while Training the Waste Gas Fan Speed Prediction Model

According to above results, it is obtained that the highest accuracy of the model training is given by hyperparameter configuration set 6. Actual waste gas fan speed vs predicted waste gas fan speed, according to the hyperparameter configuration set 12 is shown in figure 4.12.

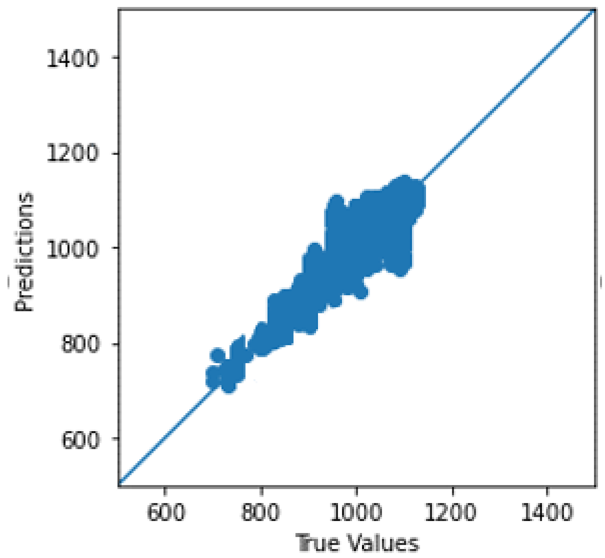


Figure 4.12: Actual Waste Gas Speed vs Predicted Kiln Rotational Speed

4.2 Model Testing in Real Time

Control variables were predicted for the real-time feature inputs in a 5 minute of interval and results were fed into the SCADA system. RKS was totally operated based on model predicted outputs for 2 hours. Stable conditions of the RKS was obtained throughout the testing period and any process parameter deviation has not been observed. Figure 4.5 illustrates the steps of real time model testing for the RKS.

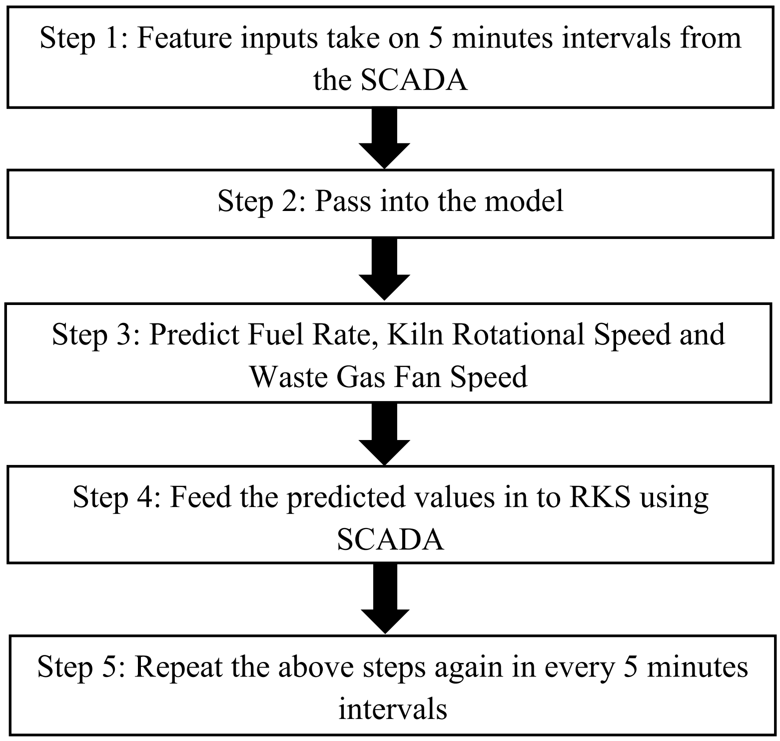


Figure 4.13: Steps of Real Time Model Testing

4.2.1 Model Predicted Values During the Real Time Testing

5 minutes intervals of model predicted values while operating the RKS in real time via model is shown in table 4.3

Table 4.4: Predicted Values from the Model while Testing Real Time

	Input Features																	Model Predictions		
Time	Feed Rate	Fuel Rate	Kiln Speed	WGF Speed	P/H CO	P/H O2	P/H NOx	3rd CN Pressure	3rd CN Temp.	4th CN Pressure	4th CN Temp.	Kiln Inlet Pressure	Kiln Current	Grate Drive Speed	AF Rate	HFO Rate	Waste Oil Rate	Fuel Rate	Kiln Speed	WGF Speed
4:00 PM	62	3750	1.65	1000	764	4.62	53	218	634	109	802	28	190	7.2	5000	0	0	3825	1.78	1012
4:05 PM	62	3750	1.78	1012	984	4.52	102	203	631	111	798	29	181	7.2	5000	0	0	3862	1.79	1001
4:10 PM	62	3862	1.79	1001	880	4.62	82	219	629	107	796	28	194	7.2	5000	0	0	3804	1.79	1008
4:15 PM	62	3804	1.79	1008	590	4.86	86	212	630	105	790	27	186	7.2	5000	0	0	3830	1.79	1006
4:20 PM	62	3830	1.79	1006	544	4.91	155	211	631	107	786	28	194	7.2	5000	0	0	3777	1.79	1007
4:25 PM	62	3777	1.79	1007	799	4.62	212	201	634	104	791	28	190	7.2	5000	0	0	3754	1.8	993
4:30 PM	62	3754	1.8	993	995	4.47	336	224	634	101	796	28	191	7.2	5000	0	0	3547	1.79	998
4:35 PM	62	3547	1.79	998	938	4.47	147	214	629	111	792	28	193	7.2	5000	0	0	3744	1.78	999
4:40 PM	62	3744	1.78	999	590	4.76	150	210	631	106	796	29	194	7.2	5000	0	0	3750	1.79	1003
4:45 PM	62	3750	1.79	1003	972	4.76	127	217	639	108	806	28	192	7.2	5000	0	0	3808	1.78	1016
4:50 PM	62	3808	1.78	1016	752	4.67	257	209	639	103	804	29	189	7.2	5000	0	0	3761	1.79	999
4:55 PM	62	3761	1.79	999	1146	4.67	175	201	642	103	807	28	186	7.2	5000	0	0	3762	1.8	1002
5:00 PM	62	3762	1.8	1002	741	4.76	167	208	642	105	807	29	191	7.2	5000	0	0	3774	1.79	1007
5:05 PM	62	3774	1.79	1007	509	4.96	175	219	643	103	809	30	190	7.2	5000	0	0	3771	1.79	1013
5:10 PM	65	3771	1.79	1013	486	4.92	151	222	644	117	804	28	187	7.2	5000	0	0	3918	1.79	1029
5:15 PM	65	3918	1.79	1029	405	5.1	147	211	636	110	807	30	188	7.2	5000	0	0	3992	1.8	1020
5:20 PM	65	3992	1.8	1020	486	4.96	135	195	634	114	809	30	192	7.2	5000	0	0	3987	1.8	1014
5:25 PM	65	3987	1.8	1014	509	4.96	212	205	635	110	806	30	188	7.2	5000	0	0	3860	1.8	1012
5:30 PM	65	3860	1.8	1012	660	4.86	122	224	632	101	804	29	182	7.2	5000	0	0	3887	1.8	1019
5:35 PM	65	3887	1.8	1019	544	4.86	212	214	632	107	806	29	180	7.2	5000	0	0	3860	1.8	1010
5:40 PM	65	3860	1.8	1010	660	4.72	131	215	625	107	802	30	180	7.2	5000	0	0	3863	1.8	1012
5:45 PM	65	3863	1.8	1012	590	4.86	122	219	624	104	800	28	183	7.2	5000	0	0	3890	1.8	1015
5:50 PM	67	3890	1.8	1015	718	4.91	192	205	627	114	800	29	187	7.2	5000	0	0	3926	1.8	1014
5:55 PM	67	3926	1.8	1014	822	4.72	110	208	623	110	804	31	185	7.2	5000	0	0	3970	1.8	1019
6:00 PM	67	3970	1.8	1019	1262	4.47	131	219	622	105	804	29	178	7.2	5000	0	0	3959	1.8	1021

Graphs are taken from the plant automation system during the real-time testing is illustrated in figure 4.14, figure 4.15 and figure 4.16

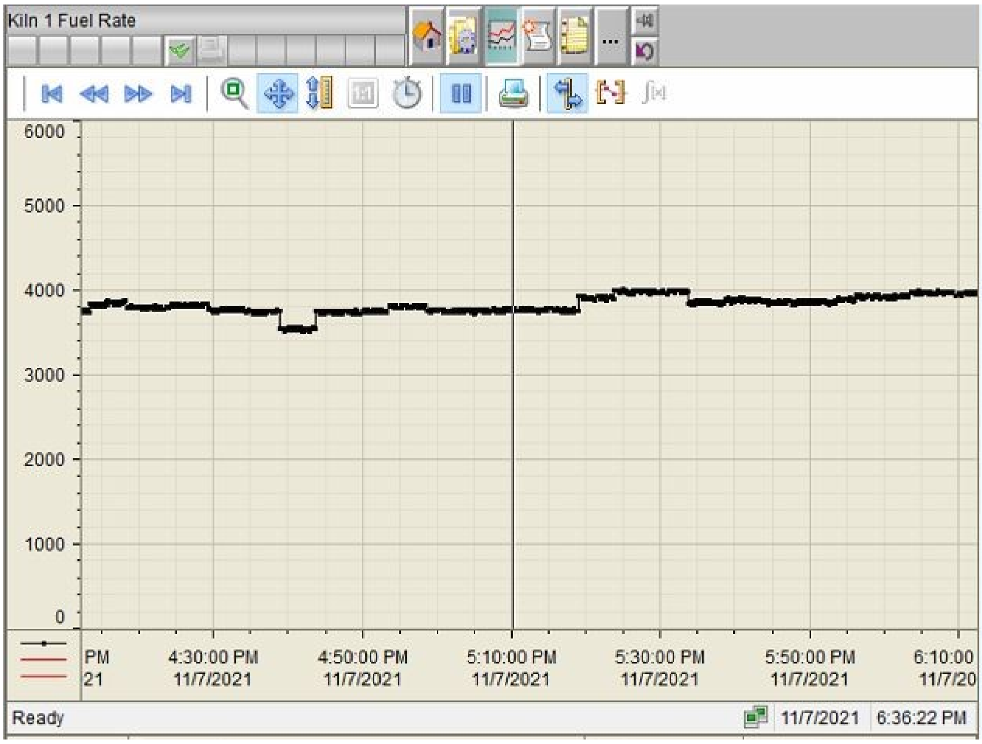


Figure 4.14: Model Predicted Output for Fuel Rate

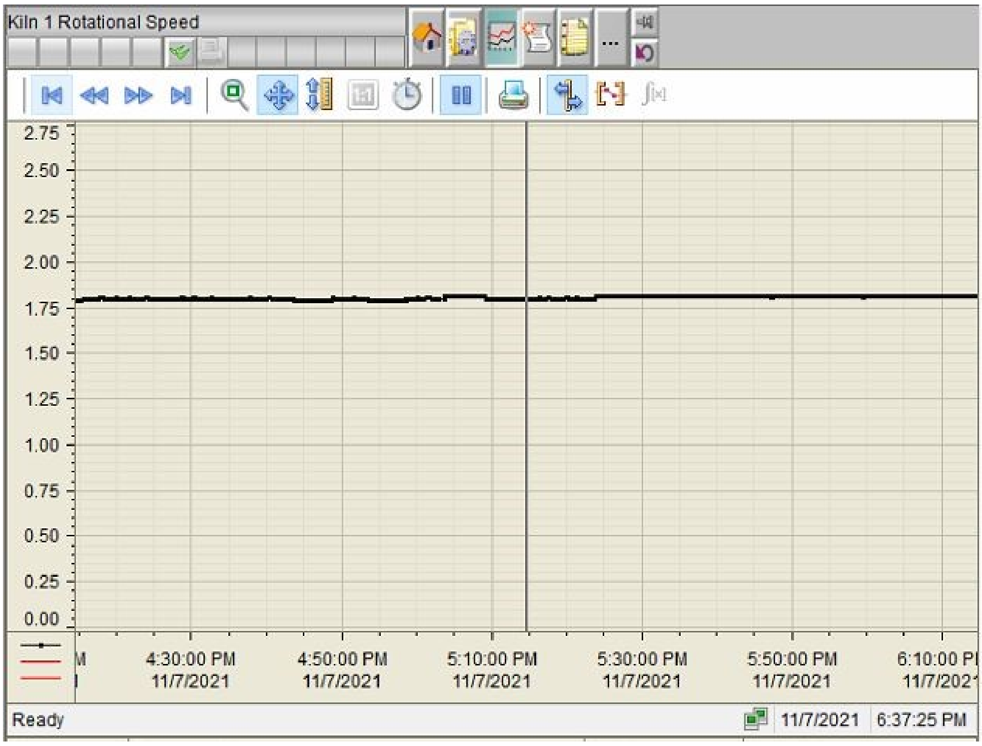


Figure 4.15: Model Predicted Output for Kiln Rotational Speed

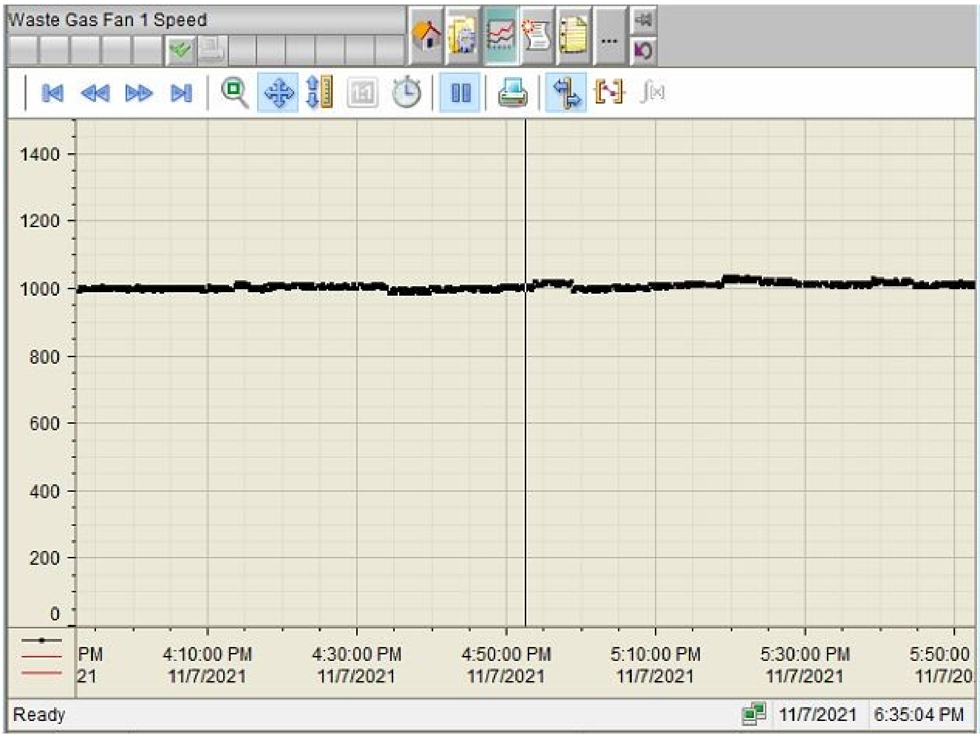


Figure 4.16: Model Predicted Output for Waste Gas Fan Speed

4.3 Model Validation

Model validation for real time operation is performed under three different measurements using recorded data. For maintain the stable condition inside the RKS all the process parameters should be varied within standards limits. Also, the production quality measurements should be adhered within their standard limits. Pyrometer is a special camera which is used to observe the temperature measurement and video inside the kiln. By analyzing visually also it can be ensured the stable conditions inside the kiln during the real-time operation.

4.3.1 RKS Process Performance Validation

For the real-time validation described below, a set of standard operating ranges for RKS process parameters found in the literature [6][9][10][28] is used (see Appendix A). This set of operating ranges of process parameters included Preheater CO, Preheater Oxygen, 3rd Cyclone Pressure, 3rd Cyclone Temperature, 4th Cyclone Pressure, 4th Cyclone Temperature, Kiln Inlet Pressure, Kiln Inlet Ampere.

Real time process parameters were plotted against the three control variables which were predicted by the model.

Preheater CO

Preheater CO variation under real time model testing is as shown as figure 4.17

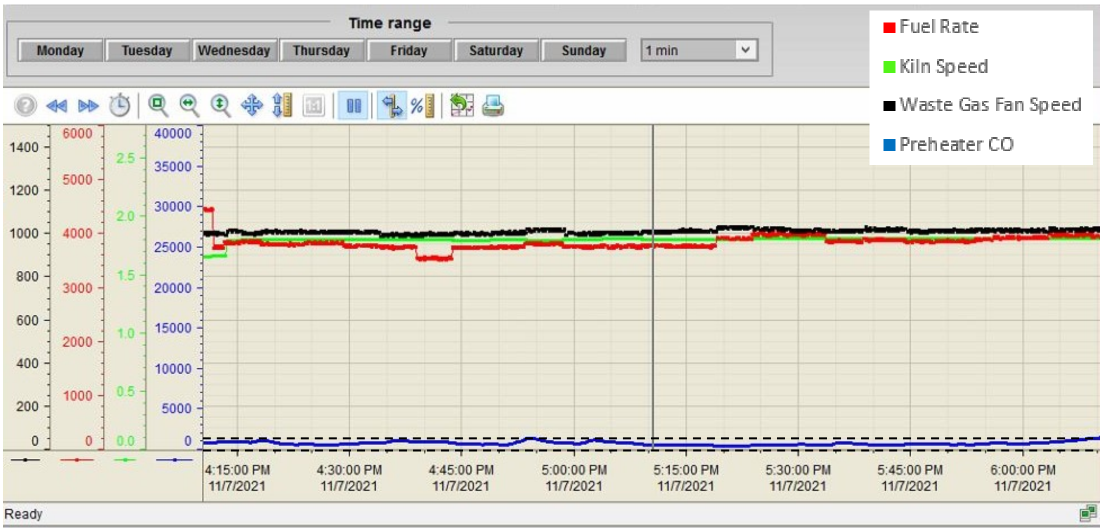


Figure 4.17: Preheater CO Variation while Real Time Model Testing

Preheater CO varies approximately between 0ppm and 1000ppm. The initial preheater CO was 752ppm at 4.00 pm. The variation of preheater CO is observed as expected.

Preheater O2

Preheater O2 variation under real time model testing is as shown as figure 4.18

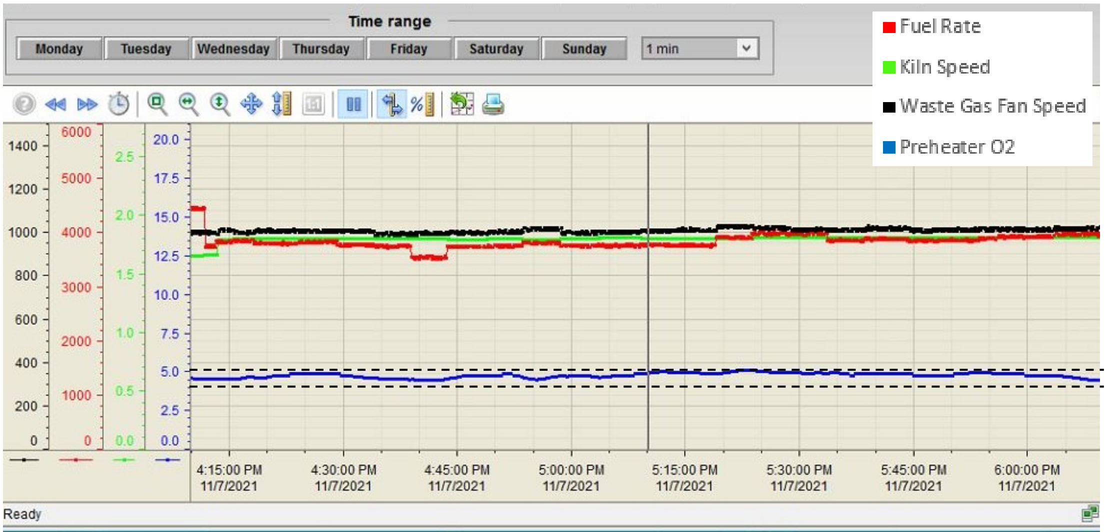


Figure 4.18: Preheater O2 Variation while Real Time Model Testing

Preheater O2 varies approximately between 4% and 5%. The initial preheater O2 was 4.62% at 4.00 pm. The variation of preheater O2 is observed as expected.

3rd Cyclone Pressure

3rd Cyclone Pressure variation under real time model testing is as shown as figure 4.19

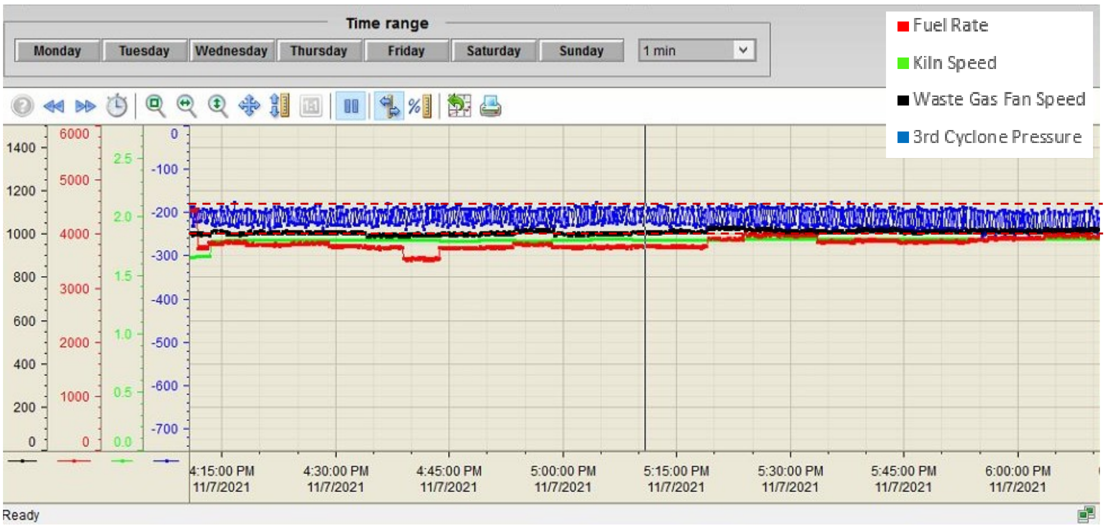


Figure 4.19: 3rd Cyclone Pressure Variation while Real Time Model Testing

3rd cyclone pressure varies approximately between -180 mmH2O and -250 mmH2O. The initial 3rd cyclone pressure is -160 mmH2O at 4.00 pm. The variation of 3rd cyclone pressure is observed as expected.

3rd Cyclone Temperature

3rd cyclone temp. variation under real time model testing is as shown as figure 4.20

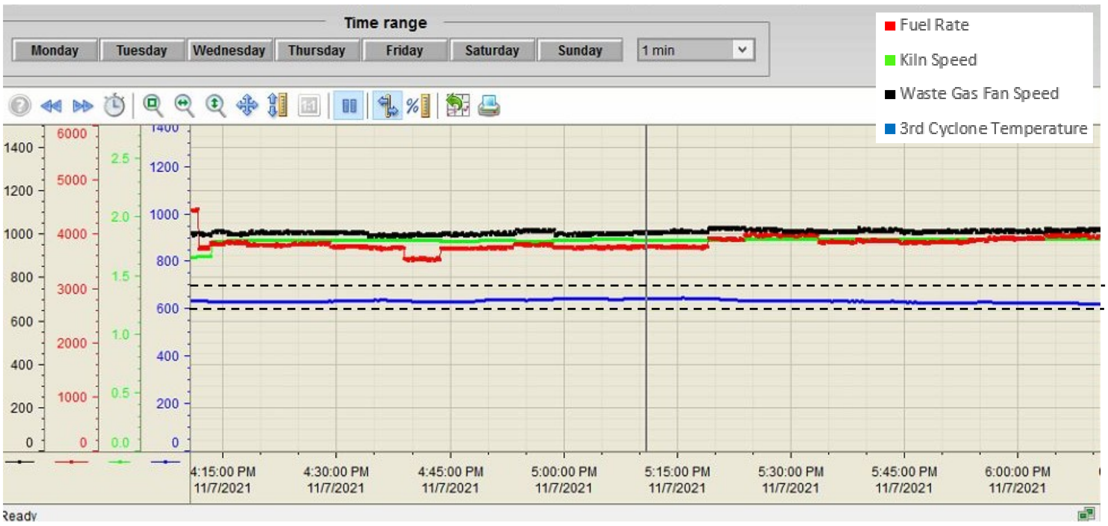


Figure 4.20: 3rd Cyclone Temperature Variation while Real Time Model Testing

3rd cyclone temperature varies approximately between 600 ºC and 700 ºC. The initial 3rd cyclone temperature is 632 ºC at 4.00 pm. The variation of 3rd cyclone temperature is observed as expected.

4th Cyclone Pressure

4th cyclone pressure variation under real time model testing is as shown as figure 4.21

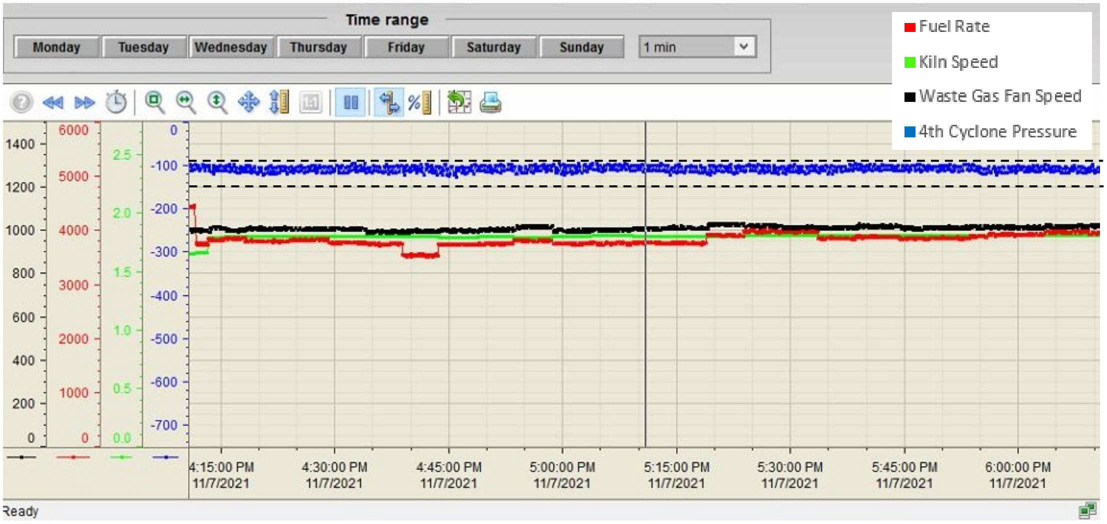


Figure 4.21: 4th Cyclone Pressure Variation while Real Time Model Testing

4th cyclone pressure varies approximately between -90 mmH2O and -150 mmH2O. The initial 4th cyclone pressure is -106 mmH2O at 4.00 pm. The variation of 4th cyclone pressure is observed as expected.

4th Cyclone Temperature

4th cyclone temp. variation under real time model testing is as shown as figure 4.22

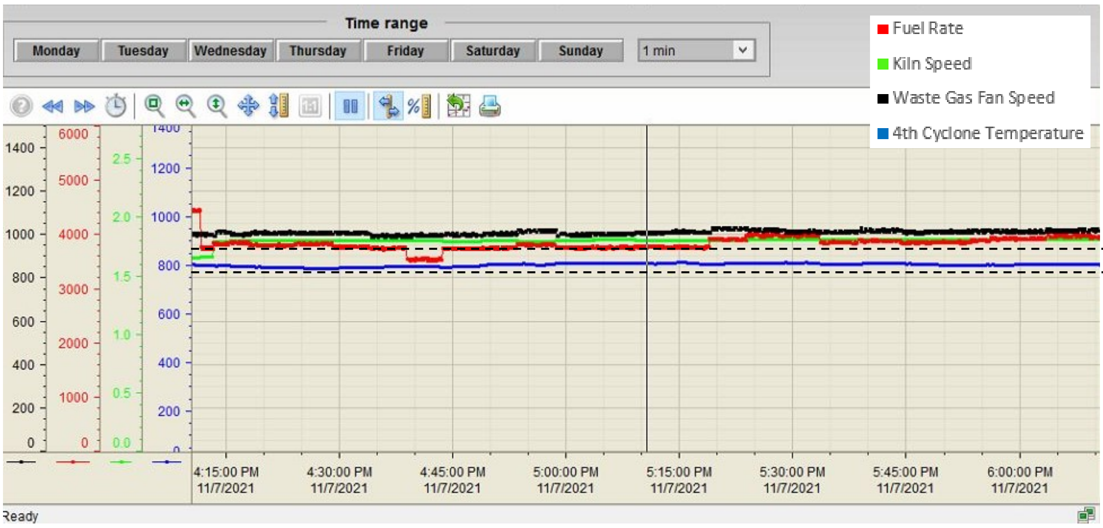


Figure 4.22: 4th Cyclone Temperature Variation while Real Time Model Testing

4th cyclone temperature varies approximately between 770 ºC and 870 ºC. The initial 4th cyclone temperature is 801 ºC at 4.00 pm. The variation of 4th cyclone temperature is observed as expected.

Kiln Inlet Pressure

Kiln inlet pressure variation under real time model testing is as shown as figure 4.23

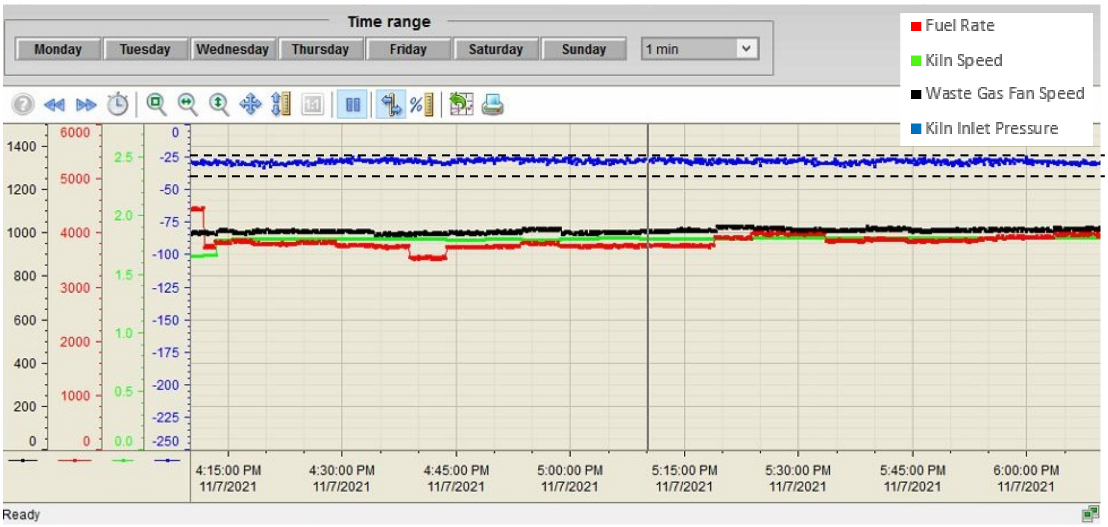


Figure 4.23: Kiln Inlet Pressure Variation while Real Time Model Testing

Kiln inlet pressure varies approximately between -25mmH2O and -40mmH2O. The initial kiln inlet pressure is -27mmH2O at 4.00 pm. The variation of kiln inlet pressure is observed as expected.

Kiln Ampere

Kiln main drive ampere variation under real time model testing is as shown as figure 4.24

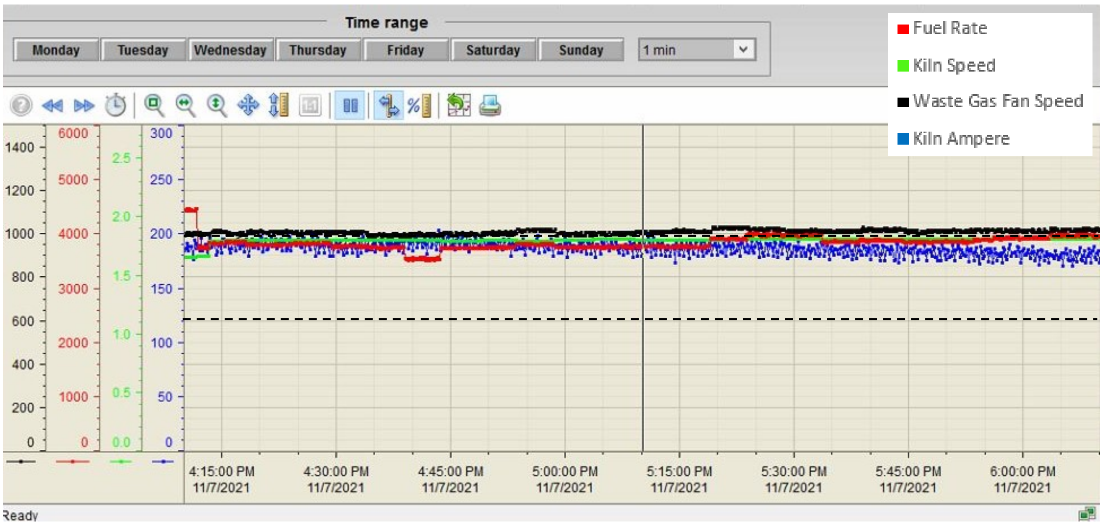


Figure 4.24: Kiln Ampere Variation while Real Time Model Testing

Kiln ampere varies approximately between 120A and 190A. The initial kiln ampere is 185A at 4.00 pm. The variation of kiln ampere is observed as expected.

According to the above figures it can be observed that during the real-time prediction all critical process parameters almost variate within the defined optimal ranges (see Appendix A) for different feed-rates. This indicates that the model predicted values are fit to the actual RKS for a stable operation.

4.3.2 Clinker Quality Analysis

Another results validation method is quality assurance of the final output from the RKS. Usually it is recommended to proceed lab test for the final product for 1-hour frequency. For the validation described below, a set of standard laboratory tests with their minimum and maximum targets for final product output of the RKS is found in the literature [6][9][10] is used (see Appendix A).

During the 2 hours of real time process validation period clinker samples were tested in 1-hour interval. Usually it takes around 40 -50 minutes to come out the clinker from the kiln after inserting raw material. The table 4.6 illustrates the lab results for the during 15.00 to 22.00 hours.

Table 4.5: Hourly Lab Test Results During the Model Testing in Real Time

Date	**Time**	**FCa0**	**LSF**	**C3S**
7/11/2021	15:00	1.30	96.5	61.2
7/11/2021	16:00	1.90	97.3	62.5
7/11/2021	17:00	1.58	96.8	63.8
7/11/2021	18:00	1.47	96.3	60.2
7/11/2021	19:00	2.01	95.8	63.7
7/11/2021	20:00	1.53	95.3	63.8
7/11/2021	21:00	0.98	96.2	61.9
7/11/2021	22:00	1.82	97.7	62.0

Usually, raw material input at 16.00 hours will come out from the RKS as the final product at around 16.40 to 16.50 hours. So, here it is considered 4 hours period of results to validate the quality requirement. According to the table 4.3 it is observed that during 16.00 to 20.00 hours all the quality parameters FCaO, LSF and C3S are within the defined range. This indicates that during the real-time validation of the model, clinker is formed within the acceptable ranges of quality parameters.

4.3.3 Pyrometer Measurement

As stated before, stability of the RKS is reflected by the pyrometer measurements. While temperature readings are within the stable ranges, the images inside the kiln also illustrate the present condition of the kiln. Figure 4.25 shows the snapshot of the kiln pyrometer during the real-time operation.

There are four zones are defined for the calcination process: calcination area, transition zone, clinkering zone and cooling zone. For the calcination process kiln temperature is needed around 1450 ºC and flame temperature is around 1650 ºC - 2000 ºC [27]

Figure 4.25: Pyrometer Snapshot while Testing the Model in Real Time

According to the figure 4.25, it is observed that the kiln inside temperatures are in acceptable ranges while the image reflects a stable condition inside the kiln.

4.4 Efficiency and Energy Consumption Improvement

4.4.1 Efficiency Improvement Calculation

RKS operators use typical values for the waste gas fan speed during the operation. While model is tested in real time, it is observed that the predicted values from the model is considerably lesser than the typical values. For the 62 t/h kiln feed rate the typical waste gas fan speed is defined as 1020 rpm. But, in the real-time validation (7th of November 2021, at 16.00 to 18.00 hours) it is predicted average value of 1004 rpm is predicted by the model for the same feed rate. Figure 4.26 illustrates the model predicted values and typical setpoints in real-time.

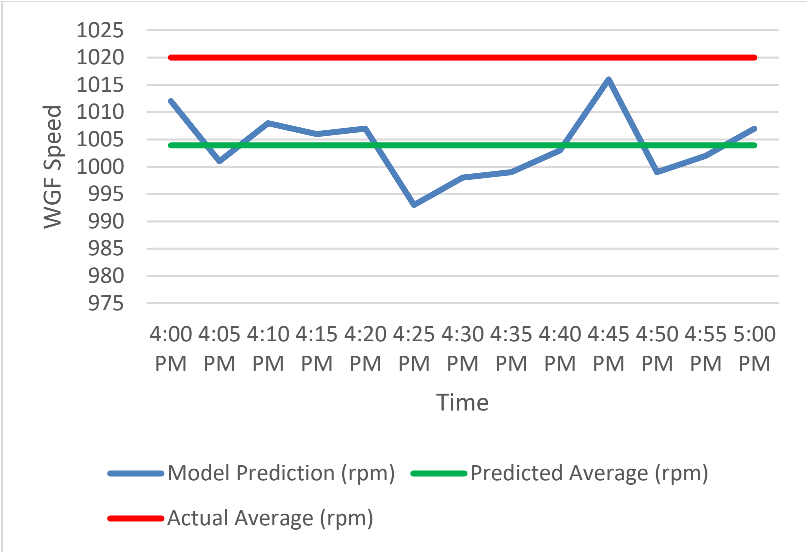


Figure 4.26: Model Predicted Values and Typical Setpoint for 62 t/h feed rate

Figure 4.27 shows the waste gas fan speed for the 62 t/h feed rate which is set by a process operator.

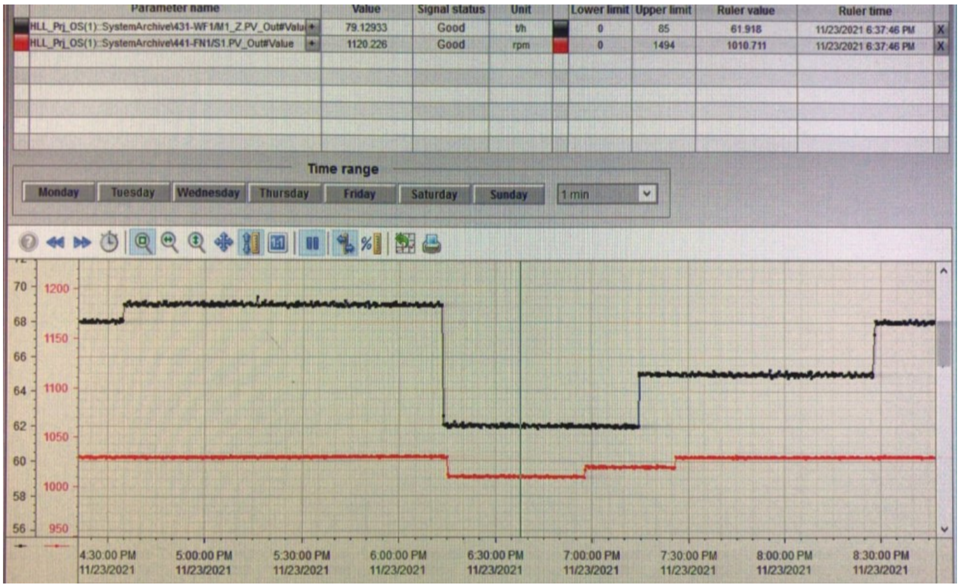


Figure 4.27: Waste Gas Fan Speed Setpoints by Kiln Operator

According to the following correlation of motor speed and power consumption, the power consumption efficiency improvement of the waste gas fan is calculated.

$$Power\ Consumption \propto Motor\ Speed^3$$

	Speed (rpm)	**Power (KW)**
Speed_Reference	1100	550
Speed_Actual	1020	439
Speed_Prediction	1003.92	333

Then, cost saving due to predicted speed for the waste gas fan is calculated as following,

Power saving (KW)	105.16
Running hours per day	24.00
Number of running days	30.00
Cost per unit (LKR)	11.20
Total cost saving per month (LKR)	848031.76

According to the above calculated values it is shown, 0.8 Mn LKR is saved per month approximately due to model predicted speed for the waste gas fan speed.

The validity of the above saving for 62 t/h, 65 t/h and 67 t/h within month of 23rd November 2021 are illustrated in figure 4.28, 4.29 and 4.30 respectively. (see appendix C)

Figure 4.28 shows the waste gas fan speeds provided by the kiln operators while RKS running at 62 t/h feed rate for 1 hour on 23rd of November from 19.00 hour to 20.00 hour.

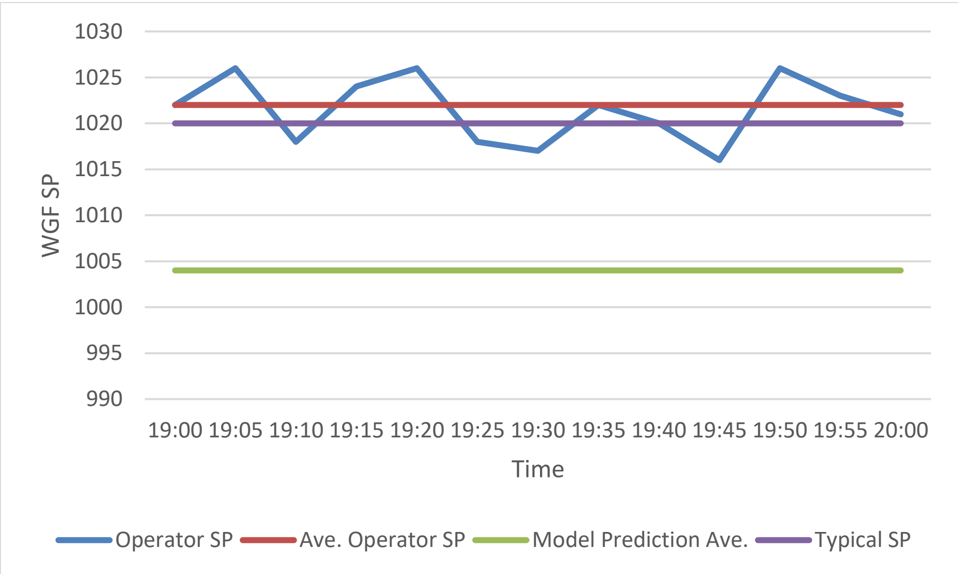


Figure 4.28: Waste Gas Fan Setpoints by Kiln Operators at 62 t/h on 23rd November

According to the above figure, it is observed that the kiln operators provide the setpoints which is always higher than the model predicted speed for the waste gas fan. Cost saving due to this speed reduction can be calculated as 0.85 Mn LKR.

Figure 4.29 shows the waste gas fan speeds provided by the kiln operators while RKS running at 65 t/h feed rate for 1 hour on 23rd of November from 20.00 hour to 21.00 hour.

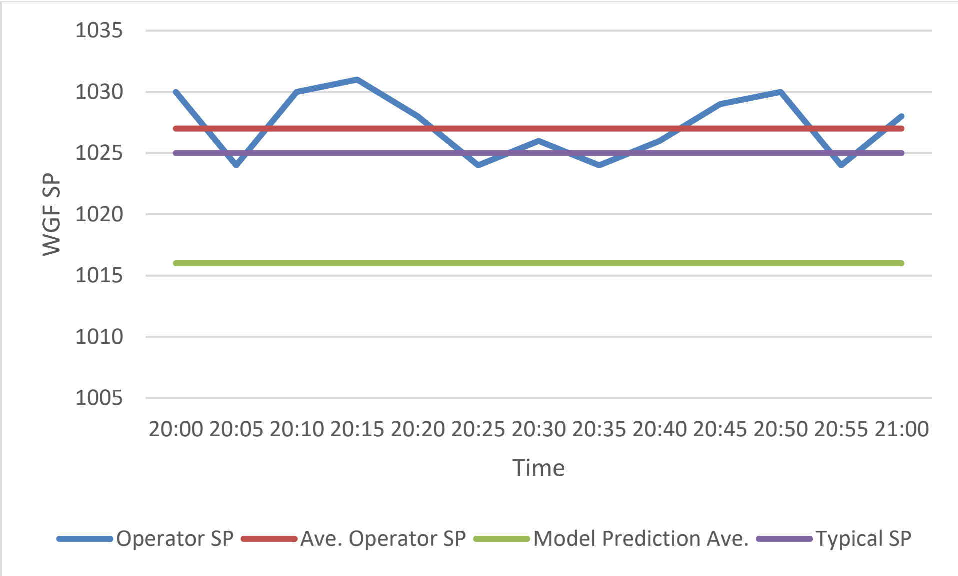


Figure 4.29: Waste Gas Fan Setpoints by Kiln Operators at 65 t/h on 23rd November

According to the above figure, it is observed that the kiln operators provide the setpoints which is always higher than the model predicted speed for the waste gas fan. Cost saving due to this speed reduction can be calculated as 0.77 Mn LKR.

Figure 4.30 shows the waste gas fan speeds provided by the kiln operators while RKS running at 67 t/h feed rate for 1 hour on 23rd of November from 16.00 hour to 17.00 hour.

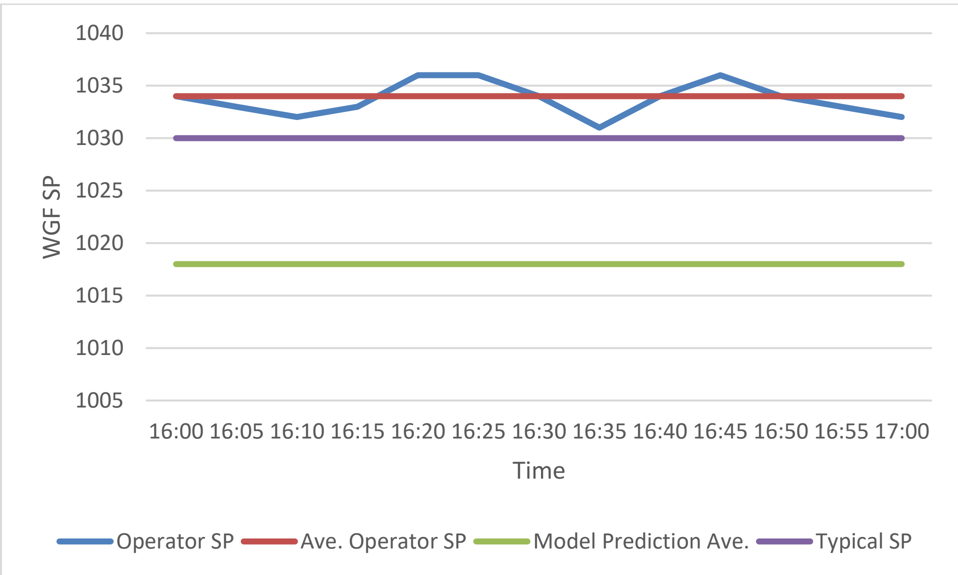


Figure 4.30: Waste Gas Fan Setpoints by Kiln Operators at 67 t/h on 23rd November

According to the above figure, it is observed that the kiln operators provide the setpoints which is always higher than the model predicted speed for the waste gas fan. Cost saving due to this speed reduction can be calculated as 0.76 Mn LKR.

4.4.2 Energy Consumption Improvement Calculation

Instead of the typical value used by kiln operators for the RKS operation, it is predicted lesser values for the fuel setpoint by the model. According to the actual operation illustrates by figure 4.32 operators used 4000 kg/h fuel rate setpoint at 62 t/h feed rate.

Also, figure 4.31 shows the model predicted fuel rate and actual fuel rate used by kiln operators at 62 t/h feed rate.

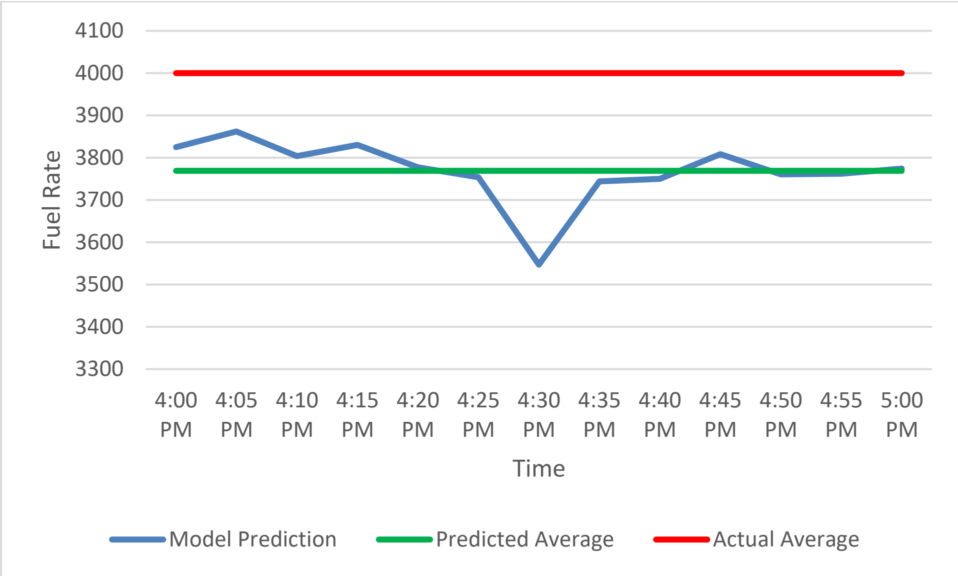


Figure 4.31: Model Predicted Values and Typical Setpoint for Fuel at 62 t/h feed rate

Figure 4.32: Fuel Setpoints by Kiln Operator

According to the figure 4.31 and figure 4.32 it is observed that 231 kg/h of fuel rate can be saved due to model predicted values. The cost saving is calculated as following,

Coal rate difference (t/day)	5.54
Coal specific energy (MJ/t_Coal)	22500.00
Daily average clinker production (t)	1120.00
Energy saving (MJ/t_clinker)	111.38
Cost per clinker ton (USD)	160.00
Total cost saving per month (LKR)/Mn	5.32

It is calculated that around 5.32 Mn LKR of cost saving per month due to model predicted values.

The validity of above saving during the month of November 2021 is illustrated in figure 4.33, figure 4.34 and figure 4.35 respectively. (see appendix D)

Figure 4.33 shows the fuel rate provided by the kiln operators vs model prediction values while RKS running at 65 t/h feed rate on 22nd of November.

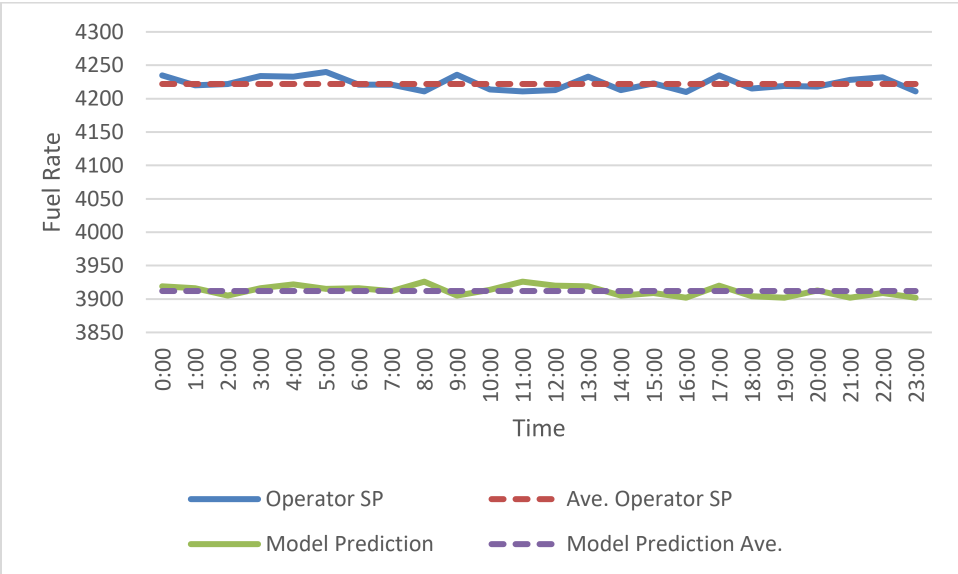


Figure 4.33: Fuel Setpoints by Kiln Operators vs model prediction at 65 t/h in 22nd of November

According to the above figure, it is observed that the kiln operators provide the setpoints which is always higher than the model predicted fuel rate. Cost saving due to this fuel setpoint reduction within the respective date can be calculated as 0.25 Mn LKR. Also, the monthly saving would be 7.14 Mn LKR.

Figure 4.34 shows the fuel rate provided by the kiln operators vs model prediction values while RKS running at 67 t/h feed rate on 08th of November.

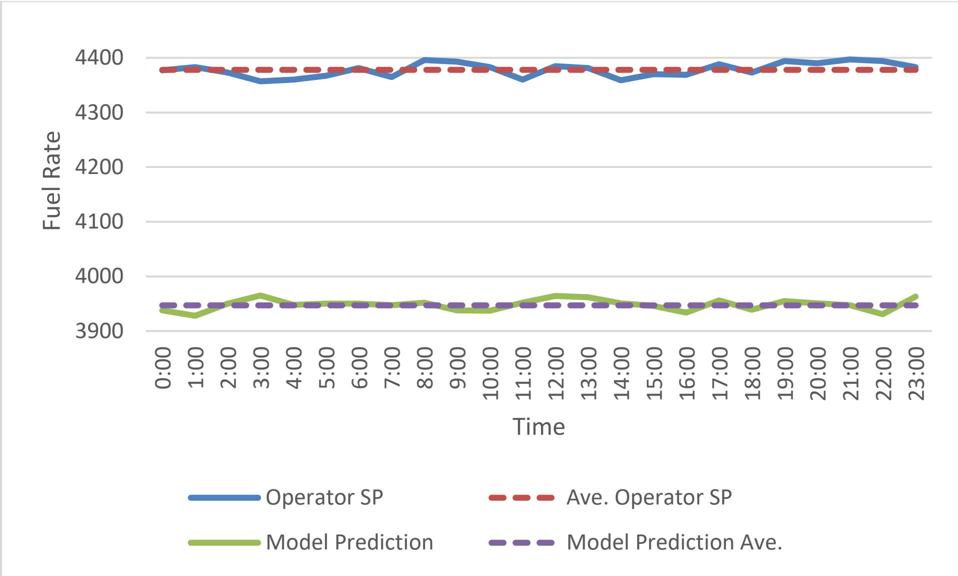


Figure 4.34: Fuel Setpoints by Kiln Operators vs model prediction at 65 t/h in 08th of November

According to the above figure, it is observed that the kiln operators provide the setpoints which is always higher than the model predicted fuel rate. Cost saving due to this fuel setpoint reduction within the respective date can be calculated as 0.31 Mn LKR. Accordingly, the monthly saving would be 9.2 Mn LKR.

Figure 4.35 shows the fuel rate provided by the kiln operators vs model prediction values while RKS running at 69 t/h feed rate on 10th of November.

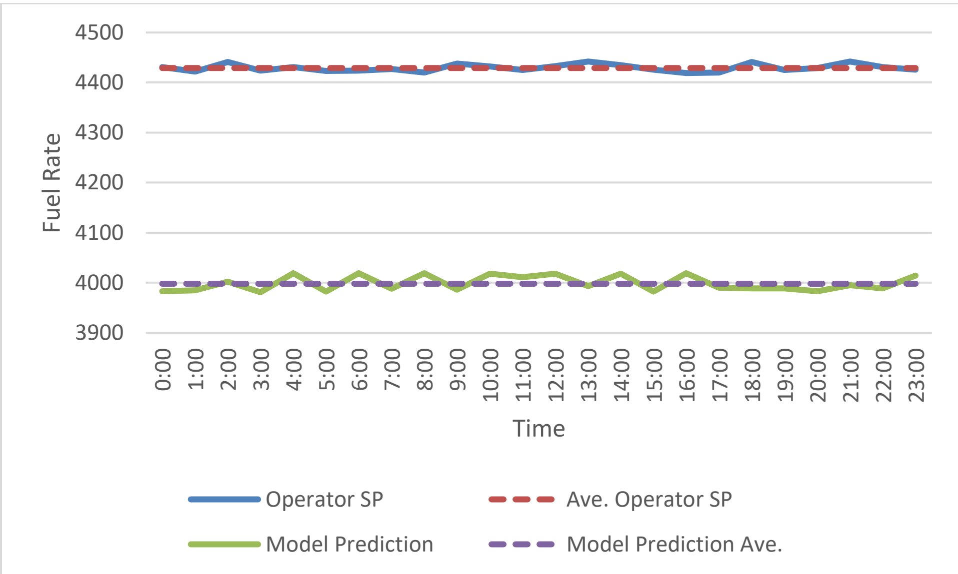


Figure 4.35: Fuel Setpoints by Kiln Operators vs model prediction at 69 t/h in 10th of November

According to the above figure, it is observed that the kiln operators provide the setpoints which is always higher than the model predicted fuel rate. Cost saving due to this fuel setpoint reduction within the respective date can be calculated as 0.33 Mn LKR. Accordingly, the monthly saving would be 9.8 Mn LKR.

4.5 Model Training and Analysis with Optimum Quality Performance Data

A set of standard laboratory tests with their target ranges for clinker production is found in the literature (see Appendix A). [6][9][10] Those ranges are having considerable gap between minimum and maximum. Now, a new dataset is considered which satisfied the following quality parameter ranges according to the table 4.6 which has a narrow range between the minimum and maximum target. Then the model is trained with the new dataset and observed the behavior of the three outputs for the real-time validation feature inputs.

Table 4.6: Reduced Ranges for Clinker Quality Parameters

Laboratory Test	Minimum Target	Maximum Target
Free Lime (FCaO)	1.2	1.6
LSF	96	98
C3S	61.5%	62.5%

Figure 4.35, figure 4.36 and figure 4.37 illustrates the original model outputs and the newly trained model output for the feature inputs of real-time validation.

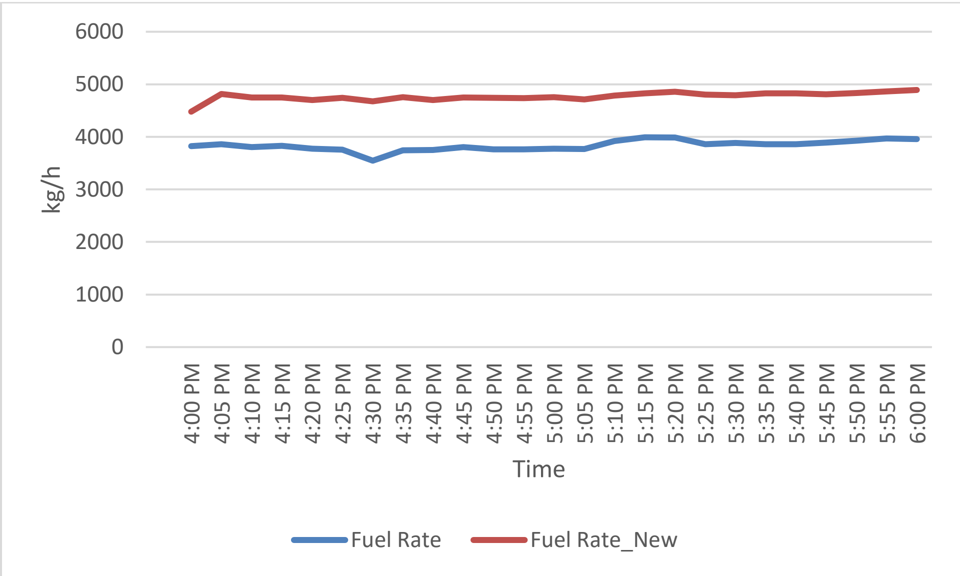


Figure 4.35: Original and New Predictions for the Fuel Rate

Figure 4.36: Original and New Predictions for the Kiln Rotational Speed

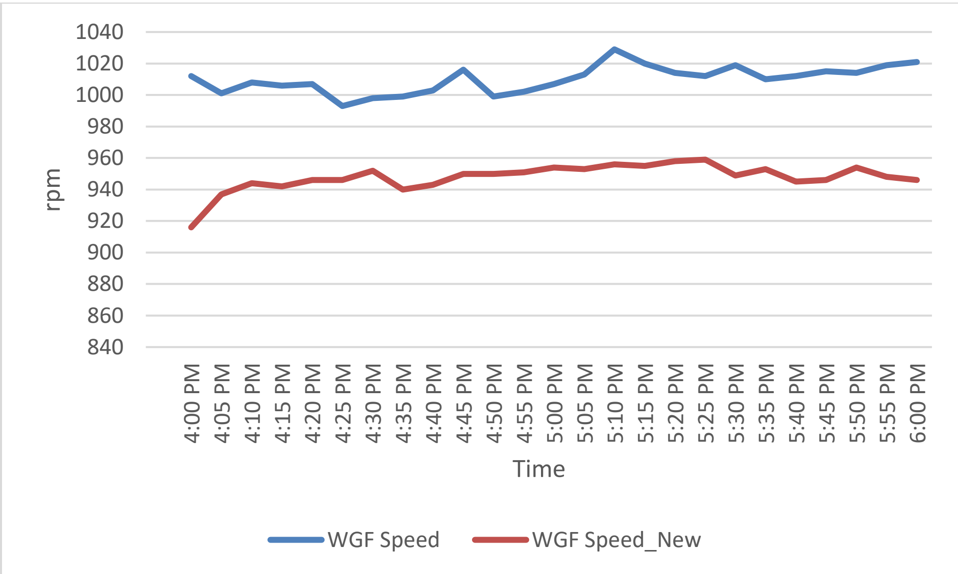


Figure 4.36: Original and New Predictions for the Waste Gas Fan Speed

In this new approach, it is observed a slight decrease of predictions of the newly trained model for waste gas fan speed and kiln rotational speed. But, it has a significant increase of the predictions for fuel rate. So, the output of the new prediction with using a narrow range of quality parameters does not give an improved output. This may cause due to the lack of data which satisfied the ranges in table 4.6 to train the model. It is an obvious, increase of the fuel rate than the standard rages are a waste of money. In conclusion, this is not a recommended approach to enhance the prediction output.

5. CONCLUSION AND FUTURE WORKS

5.1 Conclusion

The digital revolution has enabled manufacturers to introduce distributed and supervisory control systems to their plants, over the past few decades. In the heavy industry automation, these controlling systems act as the heart of the control system to achieve their production and compliance goals. Even these control systems are universal, those systems have recently begun to gain attention by artificial intelligence (AI).

Today, process operators who operates large plants such as the cement industry are expected to operate plants by their own expertise knowledge and judgment. These works are mainly carried out for one of the most important processes control systems uses in the cement industry called RKS which is used for clinker production. While the operators are monitoring massive number of process signals, they are expected to adjust process control variables (fuel rate, kin rotational speed, and waste fan speed) to maintain the process parameters within the standard range that define the stability of the kiln process. Furthermore, it is expected to troubleshoot faults, analyzing trends, perform quality tests and other documentations; thereby straining the limits of their human capacity.

Fortunately, most of the plants continuously capture and archive process data in the servers that can be actively used to implement an AI system. The use of artificial intelligence technologies for kiln process control can significantly simplify complex operations and empower operators with enhanced decision support.

The research study was proposed to build an optimum model for the automation of the kiln control process to predict fuel rate, kiln rotational speed, and waste gas fan speed. The thesis presented details of the development of that model using regression analysis via DNN in TensorFlow. The model has included three DNN Regressor estimators for the predictions of three critical process variables in clinker production which are developed choosing optimum values for hyperparameters evaluating the results for loss and matric to achieve minimum loss and error of the model. Each estimator has its own role, and works independently to perform its respective tasks. The summary of conclusions that can be drawn out of this work are:

- A comprehensive prediction model incorporating Siam City Cement (Lanka) Limited RKS process behaviors have been developed.
- The developed model is implemented using ML and DL concepts which can be defined as a regression model based on DNN.
- The developed model is validated in real-time with Siam City Cement (Lanka) Limited RKS and the validation results performed better accuracy for the three predictions, and fitted the process parameters within kiln stable range and producing clinker with expected quality.

- The proposed model is adaptable for other industrial control processes if a vast amount of data is available

5.2 Future Work

A further work will be a development of a hardware implementation for the ML model integration in to the current kiln automation process of INSEE RKS. The highlighted red square in Fig 5.1 illustrates the external work that have to be carried out for the existing process.

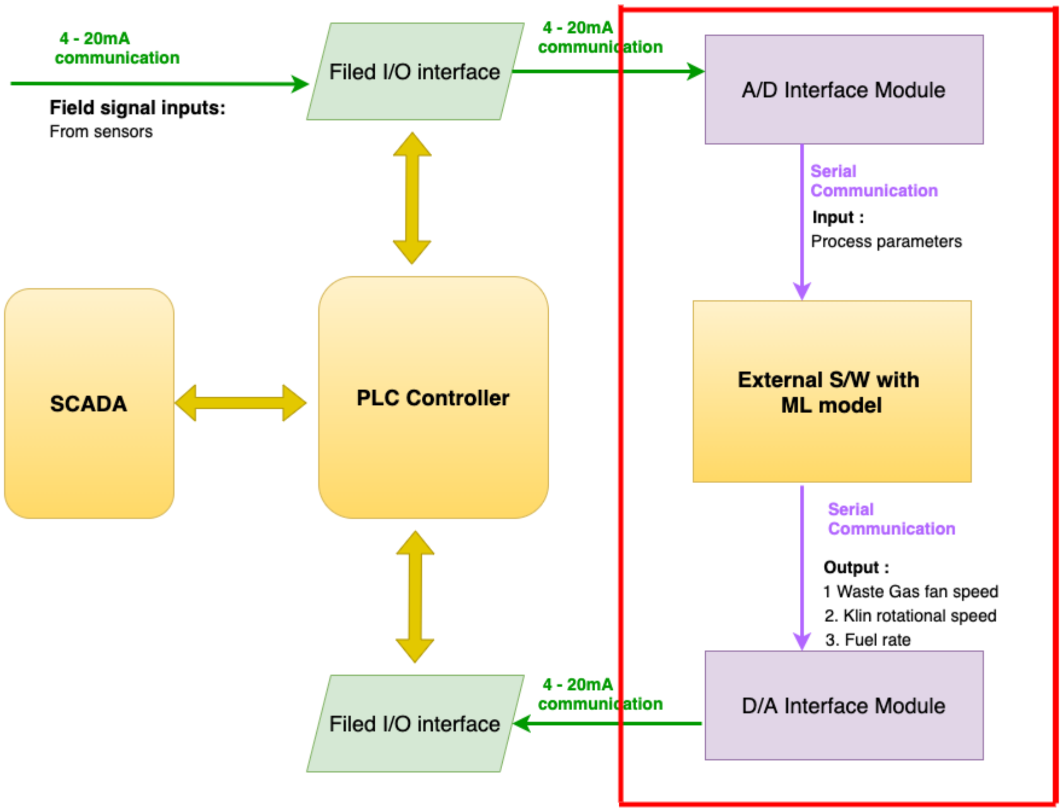


Figure 5.1: Hardware Implementation of the Research Work

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APPENDIX A - Standard Operation and Quality Targets for the RKS

Process Performance Targets

Quality performance process parameter	Optimum operating range	Unit
Preheater CO	0 - 1000	ppm
Preheater Oxygen	4 - 5	%
3rd Cyclone Pressure	180 - 250	mmH_2O
3rd Cyclone Temp.	600 - 700	ºC
4th Cyclone Pressure	90 - 150	mmH_2O
4th Cyclone Temp.	770 - 870	ºC
Kiln Inlet Pressure	25 - 40	mmH_2O
Kiln Ampere	120 - 190	A

Quality Assurance Targets

Laboratory Test	Minimum Target	Maximum Target	Type of the Test
Free Lime (FCaO)	0.8	2.2	XRD analysis
LSF	95	99	Chemical analysis
C3S	60%	64%	Chemical analysis

APPENDIX B - Laboratory Report

INSEE CEMENT

TEST REPORT

Palavi Analytical Laboratory,
Siam City Cement (Lanka) Ltd,
P.O Box 01,
Puttalam.

Product/ Material	Portland Cement Clinker
Test Report Reference	Sp/ 071121/1500-2200

Date	Time	FCaO	LSF	C3S
Chemical Properties – Xray elemental analysis				
7th of Nov 2021	15.00	1.30	96.5	61.2
	16.00	1.90	97.3	62.5
	17.00	1.58	96.8	63.8
	18.00	1.47	96.3	60.2
	19.00	2.01	95.8	63.7
	20.00	1.53	95.3	63.8
	21.00	0.98	96.2	61.9
	22.00	1.82	97.7	62.0

Prepared by:

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Sri Lanka.

APPENDIX C - Typical Values Used for Waste Gas Fan Speed and Setpoint by the Kiln Operators

Waste Gas Fan Setpoints by Kiln Operators at 62 t/h on 23rd November

Time	Operator SP	Ave. Operator SP	Model Prediction Ave.	Typical SP
19:00	1022	1022	1004	1020
19:05	1026			
19:10	1018			
19:15	1024			
19:20	1026			
19:25	1018			
19:30	1017			
19:35	1022			
19:40	1020			
19:45	1016			
19:50	1026			
19:55	1023			
20:00	1021			

Waste Gas Fan Setpoints by Kiln Operators at 65 t/h on 23rd November

Time	Operator SP	Ave. Operator SP	Model Prediction Ave.	Typical SP
20:00	1030	1027	1016	1025
20:05	1024			
20:10	1030			
20:15	1031			
20:20	1028			
20:25	1024			
20:30	1026			
20:35	1024			
20:40	1026			
20:45	1029			
20:50	1030			
20:55	1024			
21:00	1028			

Waste Gas Fan Setpoints by Kiln Operators at 67 t/h on 23rd November

Time	Operator SP	Ave. Operator SP	Model Prediction Ave.	Typical SP
16:00	1034	1034	1018	1030
16:05	1033			
16:10	1032			
16:15	1033			
16:20	1036			
16:25	1036			
16:30	1034			
16:35	1031			
16:40	1034			
16:45	1036			
16:50	1034			
16:55	1033			
17:00	1032			

APPENDIX D – Operator Setpoints and Model Predicted Setpoints on Month of November 2021

Daily Feed rate and Fuel Rate Setpoints

Date	Ave. Feed rate	Ave. Operator SP	Model Prediction Ave.
November 1, 2021	70	4445	4017
November 2, 2021	70	4435	4020
November 3, 2021	72	4460	4050
November 4, 2021	68	4400	3974
November 5, 2021	68	4395	3972
November 6, 2021	69	4420	3995
November 7, 2021	68	4400	3975
November 8, 2021	67	4378	3947
November 9, 2021	67	4350	3960
November 10, 2021	69	4425	3998
November 11, 2021	70	4440	4016
November 12, 2021	70	4440	4022
November 13, 2021	68	4410	3980
November 14, 2021	67	4358	3958
November 15, 2021	68	4405	3978
November 16, 2021	69	4422	3998
November 17, 2021	70	4435	4020
November 18, 2021	72	4455	4045
November 19, 2021	72	4457	4048
November 20, 2021	70	4444	4018
November 21, 2021	68	4397	3976
November 22, 2021	65	4222	3912
November 23, 2021	65	4225	3902
November 24, 2021	68	4400	3980
November 25, 2021	70	4442	4020
November 26, 2021	70	4440	4022
November 27, 2021	70	4443	4025
November 28, 2021	72	4460	4052
November 29, 2021	72	4462	4050
November 30, 2021	72	4460	4051

Fuel Setpoints by Kiln Operators at 65 t/h on 22nd November

Time	Operator SP	Ave. Operator SP	Model Prediction	Model Prediction Ave.
0:00	4235	4222	3919	3912
1:00	4220		3916	
2:00	4222		3905	
3:00	4234		3916	
4:00	4233		3922	
5:00	4240		3915	
6:00	4221		3916	
7:00	4221		3912	
8:00	4211		3926	
9:00	4236		3905	
10:00	4214		3914	
11:00	4211		3926	
12:00	4213		3920	
13:00	4233		3919	
14:00	4213		3905	
15:00	4223		3909	
16:00	4210		3902	
17:00	4235		3920	
18:00	4215		3904	
19:00	4219		3902	
20:00	4218		3913	
21:00	4228		3902	
22:00	4232		3909	
23:00	4211		3902	

Fuel Setpoints by Kiln Operators at 67 t/h on 08th November

Time	Operator SP	Ave. Operator SP	Model Prediction	Model Prediction Ave.
0:00	4377	4378	3938	3947
1:00	4383		3928	
2:00	4373		3950	
3:00	4357		3965	
4:00	4360		3948	
5:00	4367		3950	
6:00	4381		3950	
7:00	4365		3947	
8:00	4396		3952	
9:00	4393		3938	
10:00	4383		3937	
11:00	4360		3952	
12:00	4385		3964	
13:00	4381		3962	
14:00	4359		3951	
15:00	4370		3946	
16:00	4369		3934	
17:00	4388		3956	
18:00	4373		3939	
19:00	4394		3955	
20:00	4390		3951	
21:00	4397		3947	
22:00	4394		3931	
23:00	4383		3963	

Fuel Setpoints by Kiln Operators at 69 t/h on 10th November

Time	Operator SP	Ave. Operator SP	Model Prediction	Model Prediction Ave.
0:00	4431	4429	3983	3998
1:00	4422		3985	
2:00	4441		4002	
3:00	4424		3981	
4:00	4431		4019	
5:00	4423		3982	
6:00	4424		4019	
7:00	4427		3988	
8:00	4420		4019	
9:00	4438		3986	
10:00	4432		4018	
11:00	4425		4011	
12:00	4433		4018	
13:00	4442		3993	
14:00	4435		4018	
15:00	4426		3982	
16:00	4419		4019	
17:00	4420		3990	
18:00	4441		3989	
19:00	4425		3989	
20:00	4429		3983	
21:00	4442		3995	
22:00	4431		3989	
23:00	4426		4014	