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SYSTEM CONTROL: NEURAL NETWORK VERSUS PROPORTIONAL-INTEGRAL-DERIVATIVE ONTROLLER

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Abstract

Artificial Neural Network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information. It is the foundation of artificial I ntelligence(AI) and solves problems that would prove impossible or difficult by human or statistical standards. This project looks at the effect of replacing proportional-integral-derivative controller with ANN. The system developed was based on heat transfer in the kiln. The PID was first used to control the kiln system and its response chart recorded; then, the Artificial Neural etwork system, experimental results were determined. In conclusion, a resulting effective kiln system control were logged, which shows a uniqueness of the ANN control of the kiln over the PID control. Overshoots and undershoots were noticed in the PID compared to the Neural Network control with no overshoots and undershoots. This shows that the ANN system has an sffsctive control over the PID and consumes less time, less energy with a reduction in the final product cost. The developed system finds application in cement industry.

Keywords: Artificial Neural Network, Proportional-Integral-Derivative**,** Uniqueness, Overshoots, Undershoots, Effective

1.1 Background of the Study

An artificial neural network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information. It is the foundation of artificial intelligence (AI) and solves problems that would prove impossible or difficult by human or statistical standards. ANNs have self-learning capabilities that enable them to produce better results as more data becomes available. Artificial neural networks are built like the human brain, with neuron nodes interconnected like a web. The human brain has hundreds of billions of cells called neurons. Each neuron is made up of a cell body that is responsible for processing information by carrying information towards (inputs) and away (outputs) from the brain. An

ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapes in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

Cement production is a complex process, composed of a series of activities requiring substantial technological support. The basic process in cement production plant in baking of the raw material mix in a kiln (a long cylindrical complex tunnel). Cement kiln exhibits time-varying non-linear behavior which physical and chemical reactions occurred in the kiln. The corresponding equations have not being derived completely and accurately while a lot of present variables are discarded in the equations (Noshirvani, 2005). It is obvioustha this fact may cause some problems in designing the controller for the rotary kiln.

In the industrial sector today, Proportional-Integral-Derivative (PID) controllers are commonly used in system control. These PID controllers perform poorly in the presence of nonlinearity in the system operation, This controller in its effect, perform poorly in the phase of nonlinearity in the system operation, thereby leading time and energy wasting, giving a poor value in the final

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product and of high cost. In order to avert these problems, a better control method was developed, an Artificial Neural Network control system, to reduce to its lowest level the problems encountered with the PID controller.

Review of Related Work

(Akalp et al, 1994) reiterated that the kiln is a long and complex tunnel, generally with a cylindrical shape. The load, constituted by material pieces that have been molded and partially dried, is introduced at one of the ends and carried along the kiln at a very low speed. The input materials (MAT) are included of carbonates and silicates middle of the kiln is the firing zone, where gas burners are placed to impose the given temperature profile (Mota et al, 1993).

Noshirvani (2005) said that calcification is the first action done on the raw mill at the kiln by such high temperature. The high temperature at the burning zone melts the input materials. Then, main burning is gradually started and chemical reactions are done between silicates and the present oxygen of the air. CO gas includes the main part of the combustion smokes. Finally, the cement crystals are made and go out from the kiln as the clinker.

2.1 Artificial Neural Network

The classical controllers used in the industries are the proportional-integral- derivative (PID) controller because of their simple structure and convenience of implementation. However, PID controller can be totally ineffective when used in nonlinear and complex systems with time delays and unknown interactions, if its gains are not tuned properly (Swain and Subudhi, 1995). Usually the control of highly nonlinear and complex systems is tackled in practice by heuristics developed by experience operators. Since fuzzy logic control incorporates this heuristic rule-ofthumb very easily, this makes it easier to understand, and modify. However, compared with purely mathematical models, its stability is insufficient and its applied range is limited due to its poor static performance.

Joseph et al (2021), modelled and designed an egg incubator system that is able to incubate various types of egg within the temperature range of 35 – 40 0C was achieved. Adaptive Network based Fussy Inference Systems (ANFIS) was used in modeling and identification of numerous systems and successful results have been achieved. The development of the temperature control model was executed using Neuro- fuzzy controller, which entails the combination of neural network that predict the functionality of the egg hatchery system and fuzzy logic that act as an actuator for the system.

Neural Network

Seung-Hang and Jin-Oh (2012) used a Recurrent Neural Network (RNN) to establish a nonlinear empirical model of a cascade hydraulic actuator in a passenger car automatic transmission, which has potential to be easily incorporated in designing observers and controllers. Experimental analysis was performed to grasp key system characteristics, based on which a nonlinear system identification procedure is carried out. Extensive experimental validation of the established model suggests that it has superb one-step-ahead prediction capability over appropriate frequency range, making it an attractive approach for model-based observer/controller design applications in cement rotary kiln systems.

3.0 Method Used

3.1 Design Of The Neural Network Controller

Neural network control system are model-free estimators. ANNs began as an attempt to exploit the architecture of the human brain to perform tasks that conventional algorithms had little success with. They soon reoriented towards improving empirical results, mostly abandoning attempts to remain true to their biological precursors. Neurons are connected to each other in various patterns, to allow the output of some neurons to become the input of others. The network forms a directed, weighted graph.

3.2 Control system design

This is the final task and the last process in this research work. It can be achieved after complete analysis and research of the different control strategies and optimization approaches. Design of control system is specific task since control system represents the highest level of control in the sun tracker system. Therefore, it is a combined process with modelling and simulations.

The first step was identifying the problem with the PID controller, which is its inability to control the kiln effectively in the phase of non-linearity.

To solve this problem of the PID, the Development of Neural Network control was developed.

3.3 Artificial Neural Logic Algorithm

The following neural network algorithm is developed for this work:

i. Input determination

ii. Output determination

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iii. Target

iv. Step Size

v. Sensor

vi. Training

3.4 Simulation Software

Matlab R2007a edition environment would be used to carry out this work.

3.3.1 Input Data Training

The input and target data supplied to ANN model developed are as shown in Figure 3.1.

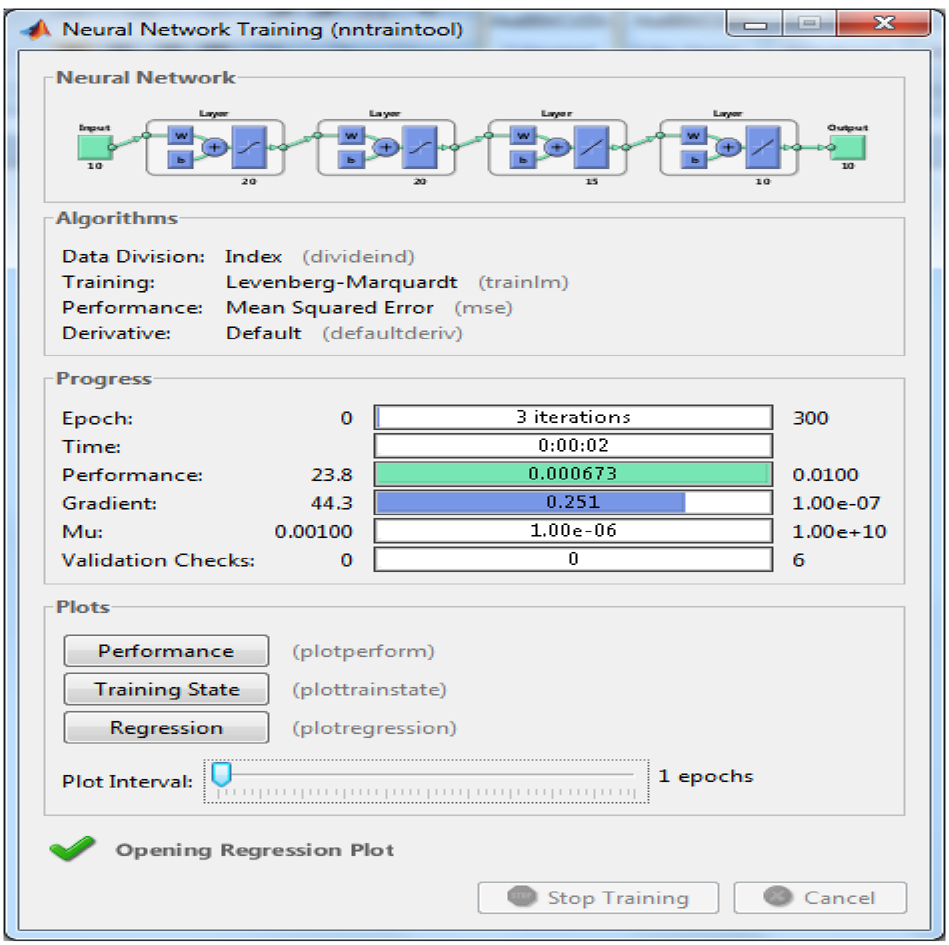

Figure 3.1: Neural Network Training

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The pm[ut target data were supplied to the neural network model, which is a four layer model and it was trained using back propagation algorithm to give the required result.

The definition of terms in Figure 2 is as shown:

Epoch: one complete presentation of data set to the iterative learning algorithm.

Time: duration for the iterative learning algorithm

Performance: translation of the input/output of the iterative learning algorithm.

Gradient: the graph of the input/output data for the iterative learning algorithm.

Mu: stands for momentum update that makes the convergence of training faster.

Nntraintool neural Inference System shows the following; Input, Layers and the Output.

The PID compensator configuration used for the kiln control is given by:

$$P + I\frac{1}{S} + D\frac{N}{1 + N\frac{1}{S}}$$

Where the initial value of P = 1, I = 1, N = 100, D = 0

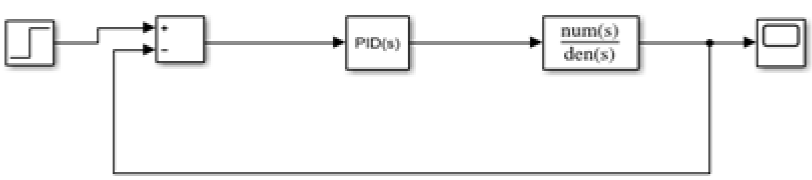

Figure 3.2: The PID configuration for the kiln contro

4.0 Results And Discussion

4.1 Result

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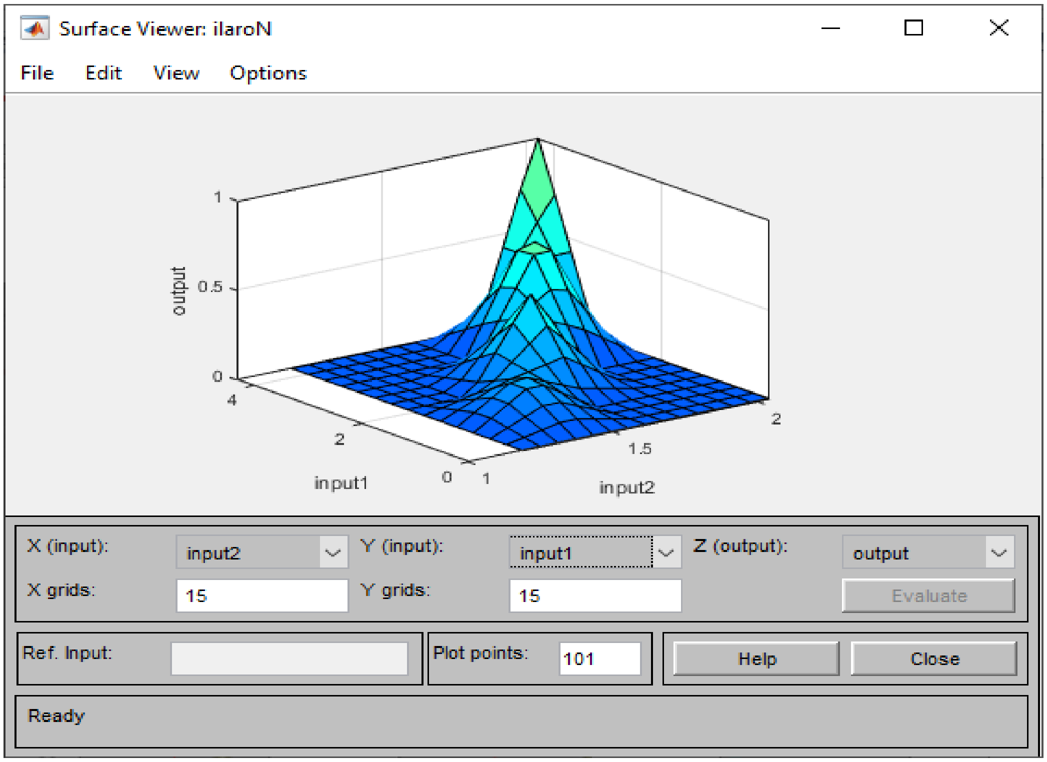

Figure 4.1: Surface of the rule base

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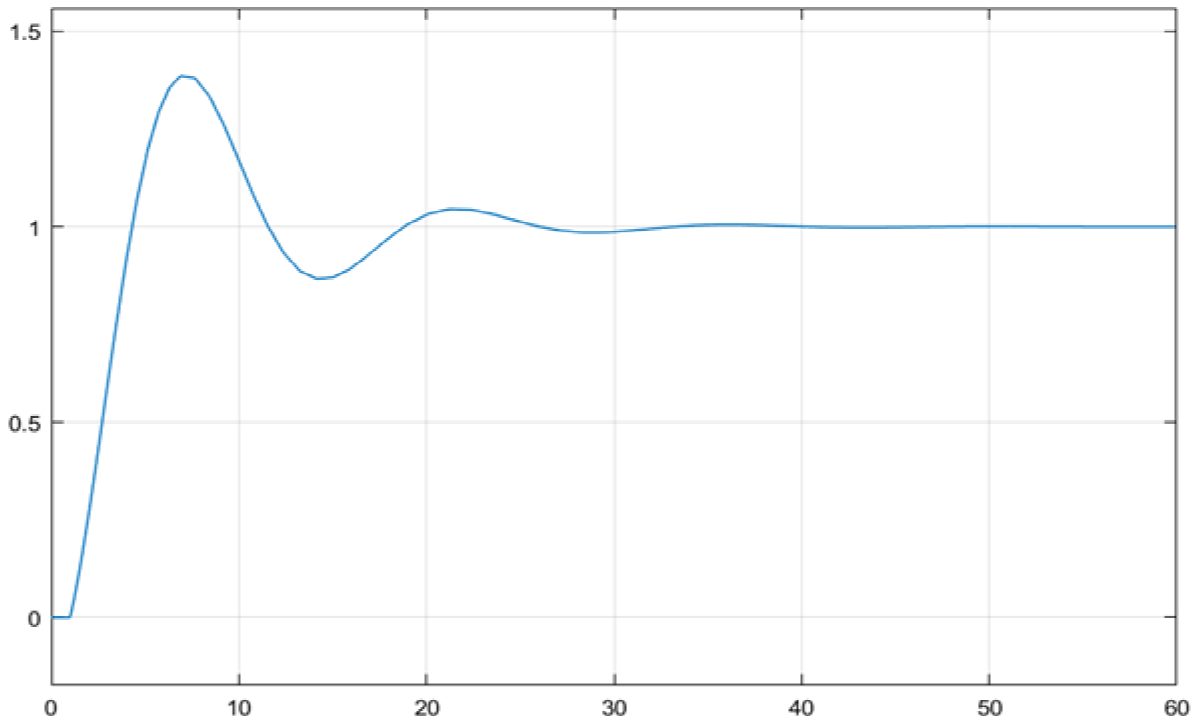

Figure 4.2: The response of the kiln based on PID controller

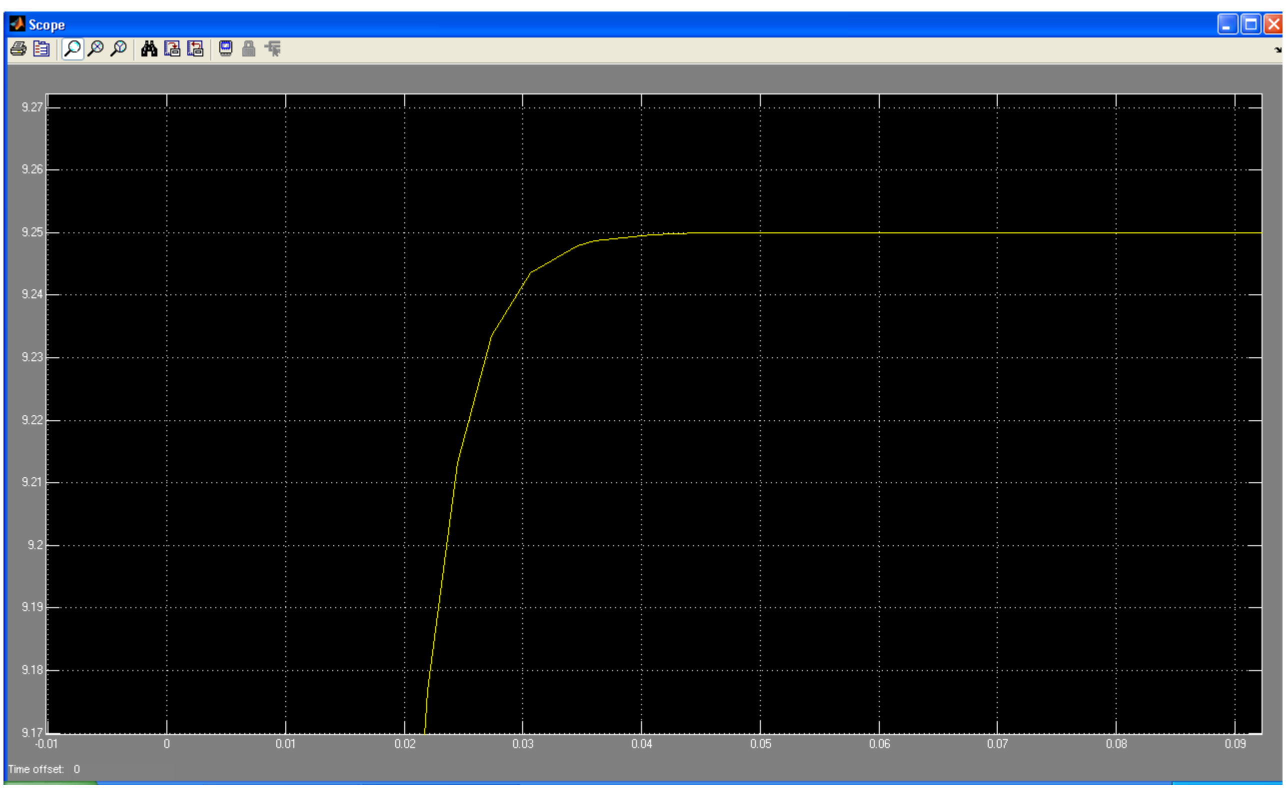

Figure 4.3: Neural Network Control

4.2 Discussion

Figure 4.1 shows the surface view of the rule base of the ANN, having two inputs and an output. As the inputs increase, the kiln operation shows significant improve.

From Figure 4.2, the PID chart experiences high overshoots, and undershoots, leading to high cost in the system production; also it has high energy consumption, high time consumption. This will generally lead to high cost in the final products of the cement

From Figure 4.3, the Artificial Neural Network chart experiences no overshoots, and undershoots, leading to low cost in the system production; also it has low energy consumption, low time consumption. This will generally lead to low cost in the final products of the cement.

5.0 Conclusion and Recommendations

5.1 Conclusion

The Neural Network model performance gave low/zero percentage overshoots and undershoots compared with the high percentage overshoots and undershoots in the PID controller, thereby solving the problem of perennial instability in the operation of rotary kiln in cement production plant. Hence, the controller protects the equipment and increases uptime, thereby giving a quality output product at reduced energy, lower maintenance costs and fewer pollution emissions. The control of the burning zone temperature of rotary cement kiln was achieved in this work, which has being a research work never being carried out before.

5.2 Recommendations

This work clearly shows numerous advantages of neural network based controllers over the conventional PID controllers. This must be incorporated in the control of kiln operation for optimal performance and autonomous operation. Appropriate kiln temperature control would lead to quality product and could bring down the production cost of Portland cement as input-output ratio is adequately maintained.

The implementation of the Neural Network controller system can easily be applied to real-time control situation in terms of the control of the rotary kiln temperature, by replacing the human tuner aspects of the PID controller with the Neural Network, so as to act as an auto-tuner to the PID controller.

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