A predictive control system for concrete plants. Application of RBF neural networks for reduce dosing inaccuracies.

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Abstract. In industry, a comprehensive control process is necessary in order to ensure the quality of a manufactured product. In the manufacturing process of concrete, the variables are dependent on several factors, some of them external, which require very precise estimation. To resolve this problem we use techniques based on artificial neural networks. Throughout this paper we describe an RBF (Radial Basis Function) neural network, designed and trained for the prediction of radial in concrete manufacturing plants. With this predictive algorithm we have achieved results that have significantly improved upon those obtained to date using other methods in the concrete industry.

Keywords: RBF, Prediction, Neural Network, Concrete, Dosing.

1 Introduction

Concrete is made up from a mixture of four materials: cement, aggregates, water and additives. The type of concrete to be manufactured is determined by a formula

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which establishes the dosage of each raw material. The materials are added from hoppers and tanks into the plant mixer. The amount of ingredients should be those contained in the formula as dosing errors are limiting and may make the mixture unusable. This problem is characteristic of a large number of processes; in [1] several methods based on anticipatory compensation are proposed to systematically reduce inaccuracies during the application of highly viscous substances.

In this paper we present a control system for concrete plants that integrates a predictive algorithm based on RBF neural networks to produce anticipatory actions that reduce dosing errors. The predictive algorithm runs in parallel with the control system and produces anticipatory actions on the gates of dispensing equipment. The predictive algorithm runs online and it is adjusted at each dosing manoeuvre.

Since the McCulloch-Pitts' model (1943) and Hebb's learning algorithm (1949), a large number of models and training algorithms have emerged. All these algorithms are characterized by the use of massive parallelism and redundancy, which makes them very robust. They are also distributed algorithms, fault-tolerant and learn through training, all characteristics that make them well suited for industrial applications. Since the late 1980s there has been considerable interest in radial basis function (RBF) neural networks, due to their good global generalization capacity and a simple network structure. RBF neural networks use radial basis functions as activation functions and have been widely applied to function approximation, prediction time and control functions. Gaussian functions are selected in the majority of cases as radial basis functions. In [2] an identification scheme for dynamic systems based on an RBF neural network is proposed. This network is trained online and dynamically adjusts its structure (number of nodes or elements in the hidden layer) allowing real time implementation of the identifier in the control loop. A performance analysis of the minimal resource allocating network (MRAN) algorithm for online identification of non-linear dynamic systems was presented in [3].

The algorithm proposed in this paper uses the time series data generated in the dosing processes of cement, aggregates, additives and water to make predictions. Some previous work proposes the use of radial basis function networks for time series prediction (see [4]). Several solutions based on RBF networks have been applied in the concrete industry to predict concrete strength. A prediction model based on an RBF network with 9 input vectors and 1 output vector is proposed in [5], to express the complex non-linear relationship of factors which affect concrete performance. As a result, this model has good generalization capacity and is highly precise as a predictive method for concrete performance.

2 System Description

The concrete plant where this predictive control system has been integrated consists of four aggregate hoppers, two cement silos, two scales, two additive feeders, a water dispenser and a mixer. The aggregate hoppers and cement silos store the aggregates and cements that are then dosed using aggregate and cement scales in the order and quantity specified by the control system. The aggregate and cement scales have loading cells which measure the amount of aggregate and cement falling from the storage hoppers and silos. The dosage of additives from the feeders into the mixer is measured by flow meters. The water is also dosed directly into the mixer and is measured by flow meters. The material from the aggregate and cement scales is mixed in the mixer with the additives and water for the length of time necessary to produce a homogeneous mixture.

Strength is the most important property of concrete, therefore, it must be controlled to meet the required specifications. The strength is determined by testing samples of produced concrete with different curing times. In [6], soft computing techniques are applied to dosing standard concrete mixes. In [7], neural networks have been applied to estimate the influence ingredient quantities have on the strength of concrete produced. Other important properties to consider are cement content and water-cement ratio.

Fig. 1 Concrete plant**.**

The concrete plant control system for tests is composed of a SIEMENS ET200S PLC, SCADA terminals, and an NI CompactRIO for historical storage operations in a batch process. NI CompactRIO PAC is connected to the PLC through a PROFIBUS communication bus and stores the values of important process variables for analysis. The PLC controls the plant according to the requested quantity of formula. In this way it achieves optimum dosing and precise amounts of different sized aggregates, cement, additives and water. The control algorithms are programmed to form a multi threaded application where each piece of equipment contains its own execution thread.

Fig. 2 Control system diagram.

Each machine at the concrete plant has an execution thread in the control algorithm, the additive feeders, cement silos, aggregate hoppers and water supply are all considered as dosing elements. Each dosing element receives the anticipative input from the RBF prediction algorithm. All the RBF predictors for every dosing element are implemented in the NI CompactRIO.

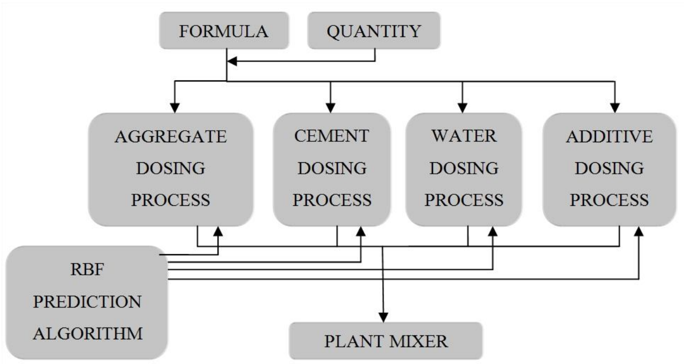

Fig. 3 Integration of the predictive algorithm with the control process algorithms.

In a dispenser, the material dosage starts with the open discharge gate command that pours the material onto the scale. The weight of material dispensed is monitored to determine the exact moment when it reaches the setpoint of the discharge gate close. The following graphs describe the material flow rate and dispensed weight over time.

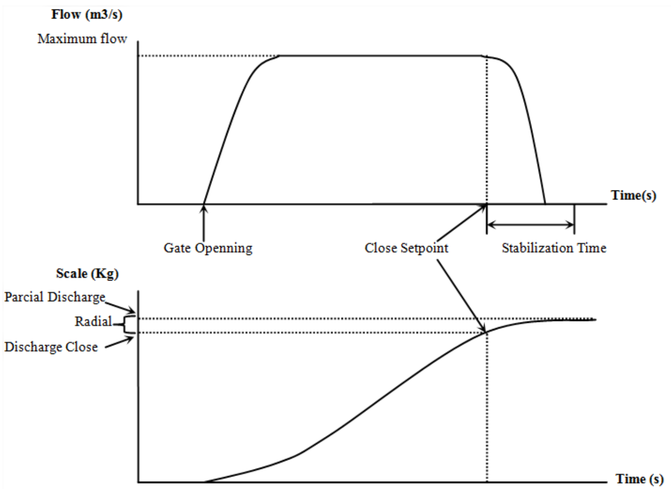

Fig. 4 Graphics flow Vs time and weight Vs time.

As noted, after the close setpoint, material dosing continues because the discharge gate close action is not instantaneous. The difference between the weight measured after a stabilization period (Partial Discharge) and the weight measured at the exact time of the close set point (Discharge Close) is the Radial of a dispensing element.

The Radial has a direct relationship to the quality of manufactured concrete and its prediction is the main subject of this article. A bad estimation of element radial causes the dosage of materials to differ from those indicated in the formula, and the concrete manufactured will be of a lower quality, or simply have different qualities to the ones specified by the formula. The following sections describe in detail the study of prediction methods used in the calculation of element radials.

Until now, the prediction of radials in our test plants has been performed using a moving average method. The estimate depends exclusively on the average of the last 10 measurements. This method has many disadvantages as it does not take into account critical factors such as moisture, the physical form of the hopper, the value of the setpoint or flow rate at the gate closing time. With this method a radial outlier negatively affects the following 10 cycles. For these reasons a more sophisticated algorithm is necessary. The RBF neural network has significantly improved these estimates as discussed in the next section.

3 Application of RBF in predicting radial.

RBF (Radial Basis Function) is a type of neural network that allows you to adjust non-linear functions. They are commonly used to classify patterns of behaviour in which the number of patterns is not too great. It is characterized by high efficiency and speed in learning.

This is the typical architecture of an RBF network:

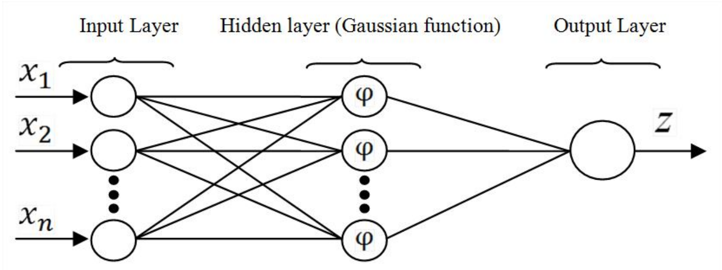

Fig. 5 Architecture of an RBF network

As shown in the diagram, RBF is divided into 3 layers: input, hidden and output. The input layer is used for data acquisition and training patterns of the network. In this layer, there are as many neurons as inputs to the network. Neurons in the hidden layer apply a Gaussian function which has two parameters: center and width. The center is the n-dimensional space (where n is the number of entries) that defines the center of gravity of the Gaussian function of the neuron. The width is used to define the standard deviation (amplitude) of the bell curve. There are various algorithms for the calculation of the centers, one of the most popular is the K-Means.

Output z of the RBF is a function of a non-linear transformation arising in the hidden layer, produced by the radial function (Gaussian function) followed by a linear transformation produced in the output layer, which adds each of the results of the hidden layer, multiplied by a factor called weights (w), which varies according to the learning process:

$$z = y(x) = \sum_{i=1}^{M} w_i \phi(\| x - c_i \|) \ , \tag{5.1}$$

where

$$\| x - c_i \| = d = \sqrt{(x_1 - c_1)^2 + (x_2 - c_2)^2 + \ldots + (x_n - c_n)^2} \ , \tag{5.2}$$

where M is the number of neurons in the hidden layer, n is the number of inputs to the RBF network (neurons in the input layer), c_i is the center of the neuron i in the hidden layer, (coordinates c_1, c_2, …, c_n), x_i is the input vector (formed by the coordinates x_1, x_2, …, x_n), d is the radial or Euclidean distance (radius from the point defined by the input vector to the center of the neuron i in the hidden layer), φ is the radial function (Gaussian), w_i is the weight factor and z, $y(x)$ is the response of RBF neural network.

When an input vector is close to the center of a neuron of the hidden layer, this neuron will have a higher weight on the output, being highest when the entry matches the center of the neuron, and lower as it moves. Gaussian function allows them to activate those neurons whose centers are closest to the input vector, and inhibiting those with more distant centers.

For the training and design of the RBF network applied to radial prediction, initially, a data matrix for training the network is built from measurements taken at the plant, having as inputs the following process variables: Error (%) Flow (kg/s), moisture (%), set point (Kg) and measured radial (Kg) for each of the cases. The data matrix used for training is:

Ta**ble 1**. Data matrix.

	Error (%)	Flow (Kg/s)	Moisture (%)	Setpoint(Kg)	Radial (Kg)
1	1,14	81	1,53	1558	11
2	1,28	83	1,58	1723	21
3	1,23	82	1,61	1324	12
4	1,14	80	2,14	1421	14
5	1,29	81	2,5	1369	11
6	1,33	84	2,63	1504	15
7	1,21	81	3,31	1578	16
8	1,14	78	3,5	1431	13
9	1,18	82	3,7	1248	12
10	1,17	82	3,71	1523	13

Below is the RBF network designed architecture:

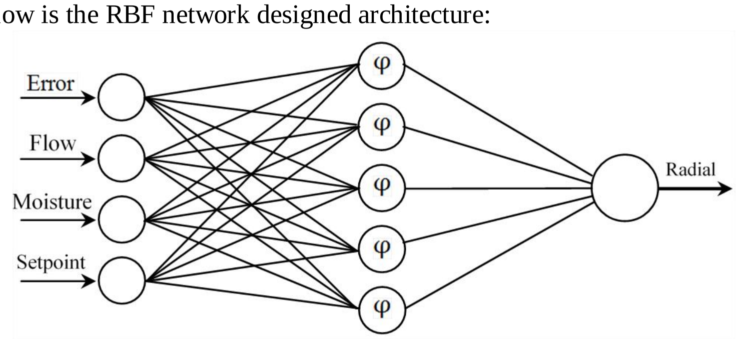

Fig. 6 RBF network designed

For the design, calculation and training of the RBF, the Model Browser tool of Matlab was used. The centers have been determined by the Rols algorithm, and these are the coordinates of each one:

Table 2. Center position

	Error (%)	Flow(Kg/s)	Moisture (%)	Setpoint(Kg)
Center 1	1.28	83.0	1.58	1723.0
Center 2	1.21	81.0	3.31	1578.0
Center 3	1.33	84.0	2.63	1504.0
Center 4	1.14	80.0	2.14	1421.0
Center 5	1.14	78.0	3.50	1431.0

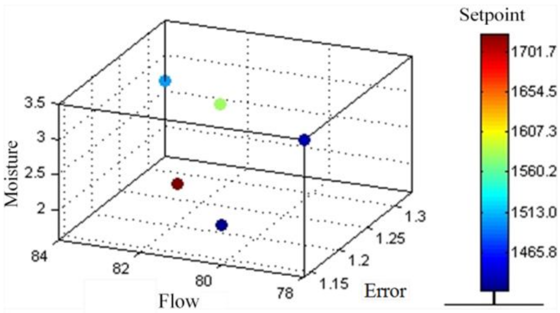

Fig. 7 Center position.

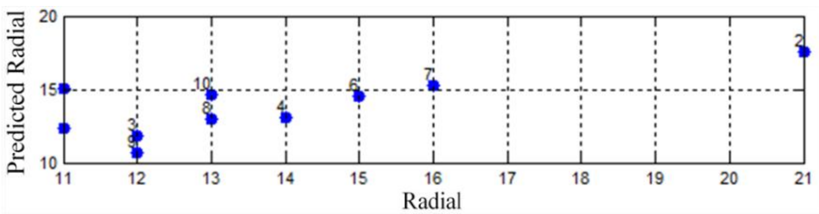

Fig. 8 Graph of Radial Vs Predicted Radial for each input vectors from matrix training

4 Results.

There is a significant improvement in the estimation of radial with the RBF neural network. Compared with the old method, moving average, the estimation accuracy has improved significantly. The RBF neural network discussed here is currently being used in our test plants with excellent results.

Shown below is a comparison between the two prediction methods used for radial estimation: moving average (old method) and RBF (current). To obtain an initial mean real radial values from Table 1 have been used.

Table 3. Process variable and predicting radial with moving average and RBF.

	Error (%)	Flow (Kg/s)	Moisture (%)	Setpoint (Kg)	Real Radial (Kg)	Predicted Radial with moving average (Kg)	Predicted Radial with RBF (Kg)
Cycle 1	1.22	82	2.13	1434	16	13	16
Cycle 2	1.31	82.1	2.13	1435	19	14	18
Cycle 3	1.28	81.7	2.14	1428	15	14	15
Cycle 4	1.20	81.4	2.14	1430	11	15	12
Cycle 5	1.32	82	2.14	1433	17	14	16

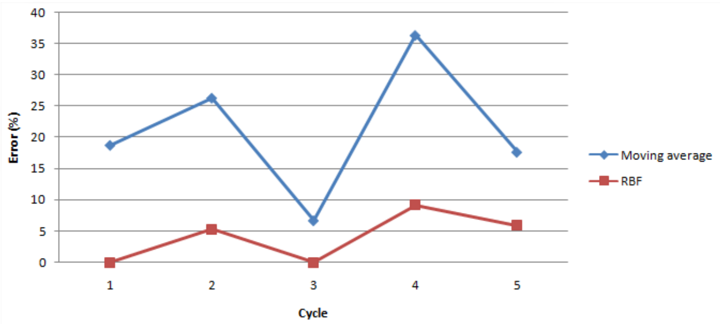

Fig. 9 Comparison of errors between moving average and RBF methods.

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