FERTILIZER QUALITY CONTROL OF A BULK-BLENDING PLANT USING INTELLIGENT SYSTEMS

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Received: January 20, 2014; Revised: April 02, 2014; Accepted: April 02, 2014

Abstract

This research aims to improve the quality of fertilizer which is produced as an important material for agriculture. Errors and loss of production often occur because of human judgment in mixing 4 types of raw materials including urea, di-ammonium phosphate, muriate of potash, and filler. In order to control the ratio of raw materials, feeding systems have to be adjusted by increasing or decreasing the conveyer speed. Therefore, intelligent systems have been developed as a supporting tool to decide how to set the parameters in the fertilizer production process. This system is built by employing artificial neural networks and fuzzy logic controllers. The results show that the overall errors of fertilizer (N-P-K) 16-16-8 and 21-7-18 have been improved by 3.22% and 10.12%, respectively.

Keywords: Neural networks, fuzzy logic, fertilizer, process control

Introduction

The current industrial agriculture system promotes reliance on agrochemicals. Therefore, developing precision agriculture has become an inevitable trend. Fertilizer is commonly used for planting and the agriculture process. Over-fertilizing causes an imbalance of nutrients and increases the cost of fertilizer. On the other hand, under-feeding of fertilizer in the planting process produces diminishing returns. The fertilizer quality usually depends on the accurate ratio of its chemical components such as nitrogen (N), phosphorus (P), and potassium (K). There are 2 styles of mixing these 3 nutrients; the first is a compound process and the second is a bulk-blending process. In the compound process, the nutrients of the fertilizer, composed of N, P, and K, are mixed homogeneously in 1 fertilizer granule, while in the bulk-blending process the nutrients of the fertilizer are in separated granules. This later is the case in the plant that was studied.

Normally the nutrients of the fertilizer will be indicated in the form N-P-K. They can be found in many kinds of raw materials such as urea, di-ammonium phosphate (DAP), muriate of potash (MOP), and filler, as shown in Figure 1. Urea (46-0-0) has 46% of N, DAP

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(18-46-0) has 18% of N and 46% of P, and MOP (0-0-60) has 60% of K. However, filler does not have these nutrients but it can be added with the types of nutrients for its special advantages. The bulk-blending process used 4 conveyer belts to mix these 4 types of raw materials, as shown in Figure 2. Entrepreneurs have a lot of problems with the fertilizer process. These problems are: 1) lack of instruments used to collect data of N, P, and K in real-time; 2) the fertilizer production process cannot be adjusted continuously while the error of chemical composition is occurring; 3) the process has to be stopped for the calibration which is a loss of time and capacity; and 4) the conveyer belts' speed is not properly set.

Improvement of the quality of the fertilizer can be started by controlling the weight of the ingredients which is reflected through the speed of the production line. There are many techniques to control the weight of materials, such as Yuan and Liaw's (1994) algorithm based on a normal proportional-integral (PI) controller and a neuro-fuzzy controller that is implemented using appropriate fuzzy rules and a neural network. Their results show that the proposed controller had both better transient and steady-state performances than those of the conventional PI controller. The second technique is an adaptive speed control for an induction motor drive using a fuzzy neural network based on the fuzzy hierarchy error

Figure 1. Raw materials

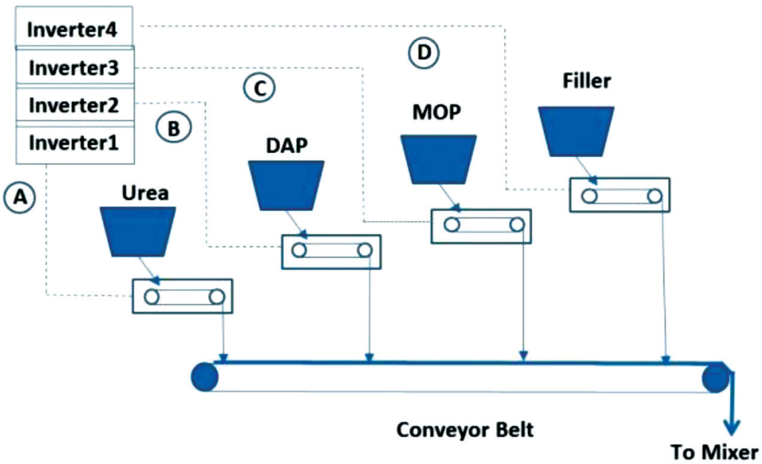


Figure 2. Bulk-blending processes using 4 conveyer belts for 4 raw materials to the mixer

approach proposed by Wu and Tam (1999). Simulation results show an improvement of fast-speed tracking and regulation. Yusuf *et al.* (2010) suggested the motor control technique for a weight-feeder control for a plastic extruder. This technique developed a system that may help users to determine the membership function of a fuzzy logic controller (FLC) using the genetic algorithm optimization. The results are better speed control and the overshoot is reduced. The fourth technique is a variable-rate fertilization control system based on fuzzy proportional-integral-derivative control strategy proposed by Chunying and Xi (2010). This method increases the control precision and reduces the static error.

This paper focuses on the improvement in the quality of production of the fertilizer using intelligent systems to decide the appropriate speed of the conveyer belt. The studied plant utilizes a bulk-blending process that employs a human operator to set the conveyer speed. The ratios of N, P, and K are often fluctuated. Therefore, this work proposes an artificial neural network (ANN) to construct a mathematical model of the fertilizer process. Consequently, an FLC is used with the above model to determine the speed setting, as shown in Figure 3. This method is developed as a supporting tool in order to decide on the conveyer speed in the studied plant.

Intelligent Systems

Artificial Neural Network (ANN)

A single layer perceptron network can be represented as

$$y_i^{(k)} = a(w_i^T x^{(k)}) = a\left(\sum_{j=1}^{m} w_{ij} x_j^{(k)}\right) = d_i^{(k)} \tag{1}$$

where $i = 1, 2, \ldots, n.$
$k = 1, 2, \ldots, p.$

where $w_i^T = [w_{i1}, w_{i2}, \ldots, w_{im}]^T$ is the weight vector associated with the process element and $a(.)$ is the activation function of the process element. A network with a single linear unit is called an adaptive linear element. The problem to be solved here is a supervised learning problem as indicated in Equation (1). For a given set of p training patterns, $\{(x^{(1)}, d^{(1)}), (x^{(2)}, d^{(2)}), \ldots, (x^{(p)}, d^{(p)})\}$, the goal is to find a correct set of weights w_i such that

$$\sum_{i=1}^{n} w_i x_i^{(k)} = d^{(k)} \tag{2}$$

where $k=1, 2, \ldots, p.$

Fuzzy Logic Controller (FLC)

The typical architecture of an FLC is shown in Figure 4.

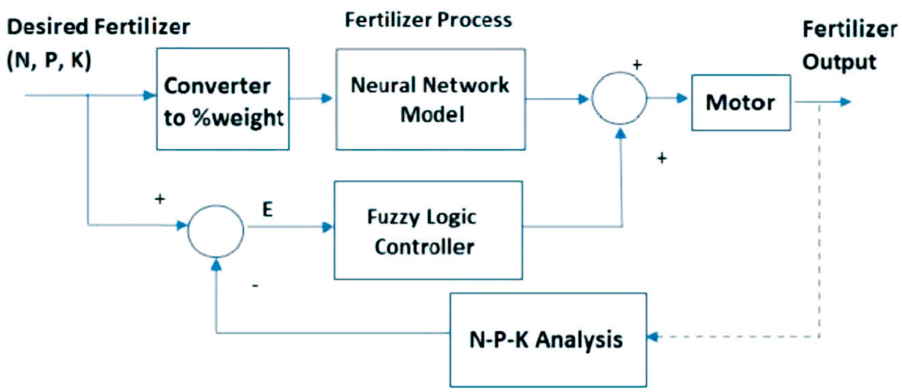


Figure 3. System descriptions

Fuzzy $\tilde{A}$ set in the universe of discourse U can be defined as a set of order pairs.

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in U\} \tag{3}$$

where $\mu_{\tilde{A}}$ (.) is called the membership function $\tilde{A}$ of and $\mu_{\tilde{A}}$ (x) is the degree of membership of x in $\tilde{A}$. The range of the membership function is a subset of nonnegative finite real numbers.

For simplicity, assume that there are 2 fuzzy control rules as follows:

R^1 *: IF x is* A_1 *AND y is* B_1*, THEN z is* C_1*,*
R^2 *: IF x is* A_2 *AND y is* B_2*, THEN z is* C_2*.*

Then the firing strengths α_1 and α_2 of the first and second rules may be expressed as

$$\alpha_1 = \mu_{A_1}(x) \wedge \mu_{B_1}(y) \tag{4}$$

$$\alpha_2 = \mu_{A_2}(x) \wedge \mu_{B_2}(y) \tag{5}$$

where $\mu_{A_1}(x)$ and $\mu_{B_1}(y)$ indicate the degrees of partial match between the user-supplied data associated with the data in the fuzzy rule base and $\wedge$ is "and operation".

$$\mu_{C_i'}(w) = \alpha_i \wedge \mu_{C_i}(w) \tag{6}$$

where i is any rule number.

The final inferred consequent is given by

$$\mu_C(w) = \mu_{C_1'} \vee \mu_{C_2'} \tag{7}$$

where $\vee$ is "or operation". This is *Mamdani's minimum fuzzy implication rule*.

Defuzzification is a mapping from a space of fuzzy control actions defined over an output universe of discourse into a space of non-fuzzy control actions. The widely used center of area strategy generates the center of gravity of the possibility distribution of a control action. In this case of a discrete universe this method yields

$$z_{COA} = \frac{\sum_{j=1}^{n} \mu_C(z_j) z_j}{\sum_{j=1}^{n} \mu_C(z_j)} \tag{8}$$

where n is the number of quantization levels of the output, z_j is the amount of control output at the quantization level j, and $\mu_C(z_j)$ represents its membership value in the output fuzzy set.

Model of Fertilizer Process

Data Gathering

The standard raw materials requirement quantity of each fertilizer product can be calculated and are shown in Table 1.

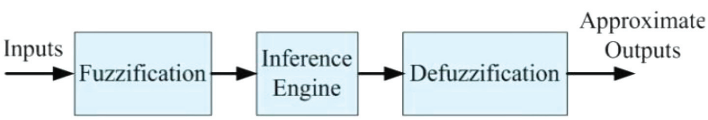


Figure 4. Fuzzy logic controller

Table 1. Raw material requirement ratio

Product N-P-K	Urea weight	DAP weight	MOP weight	Filler weight
21-7-18	40%	15%	30%	15%
16-16-8	21%	35%	13%	31%

To get the required N-P-K, the weight of each material can be determined as follow.

Weight of DAP = P/0.46 (9)
Weight of Urea = (N-Np)/0.46 (10)

where N_p is nitrogen from DAP that is equal to 0.39×P

Weight of MOP = K/0.6 (11)
Weight of Filler = 100-(9)-(10)-(11) (12)

This work considers only formulation of 21-7-18 and 16-16-8. The calibration for the inverter speed setting was done and the data are given as in Table 2.

Modeling by Artificial Neural Networks

Data from Table 2 are used to construct the artificial neural networks that represent the feeding systems of the urea, DAP, MOP, and filler, as shown in Figure 5. Therefore, the weights of the neural networks *(w1, w2, w3, w4)* and their biases were trained.

After this system was trained, *w1* is 0.1321 and *bias1* is -0.5112 for the urea belt, *w2* is 0.0276 and *bias2* is 3.1757 for the DAP belt, *w3* is 0.0604 and *bias3* is 1.3836 for the MOP belt, and *w4* is 0.0702 and *bias4* is 0.3932 for the filler belt.

Design of Fuzzy Logic Controller

The error of the fertilizer nutrients e_k

Table 2. Inverter speed setting after calibration

Product N-P-K		Urea Belt	DAP Belt	MOP Belt	Filler Belt
27-7-18	**Weight**	**40%**	**15%**	**30%**	**15%**
	Voltage	4.78	3.56	3.15	1.47
		4.80	3.55	3.14	1.48
		4.75	3.60	3.25	1.46
		4.71	3.68	3.22	1.40
		4.65	3.70	3.16	1.45
		4.86	3.50	3.17	1.47
		4.90	3.46	3.19	1.44
		4.77	3.48	3.22	1.42
		4.85	3.67	3.31	1.43
		4.66	3.69	3.15	1.45
16-6-8	**Weight**	**20%**	**35%**	**13%**	**31%**
	Voltage	2.29	4.13	2.10	2.57
		2.29	4.14	2.20	2.55
		2.32	4.15	2.05	2.54
		2.40	4.16	2.09	2.57
		2.18	4.11	2.00	2.60
		2.19	4.12	2.20	2.59
		2.20	4.18	2.25	2.54
		2.30	4.16	2.30	2.53
		2.25	4.15	2.22	2.67
		2.21	4.10	2.28	2.55

was chosen as the input of the fuzzy logic controller.

$$ek = yd - yk \tag{13}$$

where y_d and y_k are the desired and actual fertilizer nutrient, respectively. The range of e_k is selected from -2 to 2 percent from an expert opinion. The expert considers this range of e_k from a maximum acceptable value of the error.

The output of the fuzzy logic controller is z_k and is selected from -0.25 to 0.25 volt. These values also come from an expert opinion. The expert considers this range of z_k from a maximum value of output that can adjust the maximum error.

The e_k and z_k are described by 3 linguistic terms "NB (Negative Big)", "ZE (Zero)", and "PB (Positive Big)". Triangular membership functions are chosen for all the inputs and outputs, shown in Figure 6 and Figure 7.

Rules are based on an expert opinion which are

(1) IF (e_k is NB), THEN (z_k is NB)
(2) IF (e_k is ZE), THEN (z_k is ZE)
(3) IF (e_k is PB), THEN (z_k is PB)

The defuzzification center of area is used for giving the final output.

Implement and Results

The integrations of the ANN and FLC are

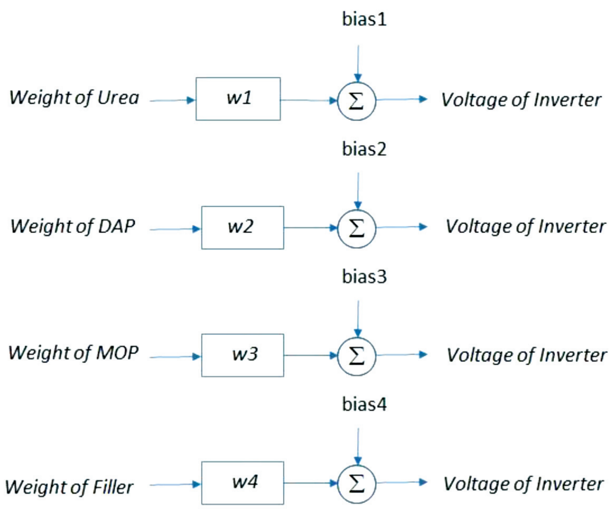


Figure 5. Neural networks representing the feeding system

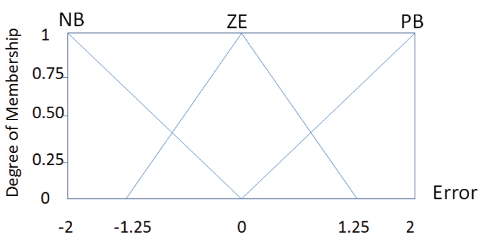


Figure 6. Linguistic terms represent FLC error

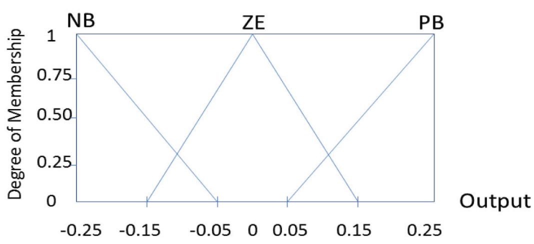


Figure 7. Linguistic terms represent FCL output

shown as Figure 8 and Figure 9. The voltage calculation results are applied to the inverter setting of the existing machines. While the fertilizer products had the error in chemical composition, the process was adjusted suddenly and no machine stopping was necessary because the calculations of the intelligent systems were used.

Steps of Program

Step 1: Applied the desired value of nitrogen (N1), phosphorus (P1), and potassium (K1) to the program.

Step 2: Initial values for each inverter setting were calculated.

Step 3: Applied the actual value of nitrogen (N2), phosphorus (P2), and potassium (K2) as feedback values from the quality control section.

Step 4: Obtained the error for the FLC.

Step 5: The FLC calculates the output voltage to compensate for these errors.

Step 6: The calculated output voltage from step 5 was added to the neural network system outputs.

Step 7: Obtained the final speed setting used to adjust the Urea, DAP, and MOP belts.

Step 8: Repeat Step3-Step7 when significant error still occurs during fertilizer processing.

Symbols in Figure 8 and Figure 9 represent as follow;

- UREA, DAP, and MOP: %Weight of Urea, DAP, and MOP, respectively.
- NN: Neural network system of Urea, DAP, and MOP belt.
- N1, P1, and K1: Desired nitrogen,

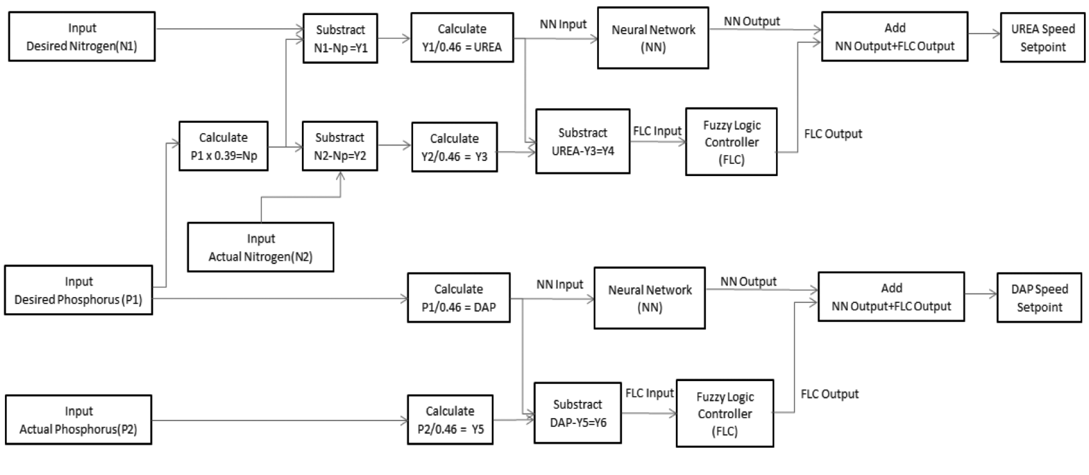


Figure 8. Integration of ANN and FLC for urea and DAP belts

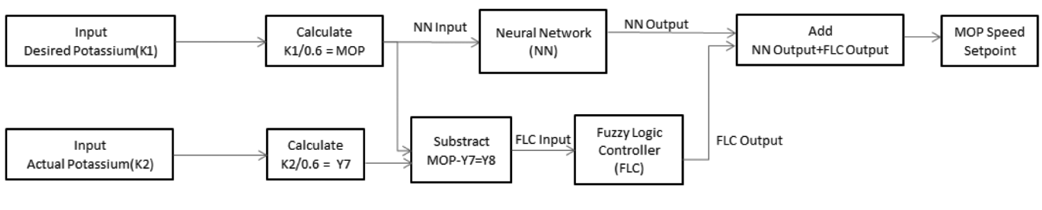


Figure 9. Integration of ANN and FLC for MOP belt

phosphorus, and potassium, respectively.

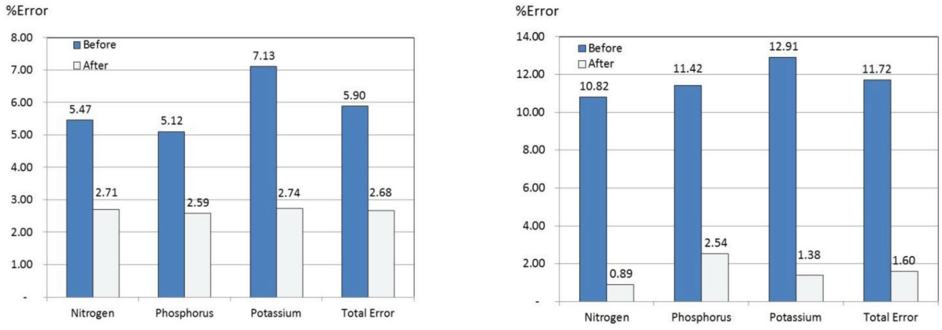
- N2, P2, and K2: Actual nitrogen, phosphorus, and potassium, respectively.

The results for the fertilizer 16-16-8 show that the errors of nitrogen, phosphorus, and potassium have decreased 2.66%, 2.53%, and 4.39%, respectively, shown in Figure 10 (a). The overall error was improved by 3.22%.

Also, in the case of fertilizer 21-7-18, the errors of nitrogen, phosphorus, and potassium have decreased 9.93%, 8.88%, and 11.53%, respectively, shown in Figure 10 (b). These give an overall error improvement of 10.12%.

The proposed systems show more reliability as the percentages of N, P, and K have less swing than the original operator speed setting, see Figures 11-13.

Before deciding to use the intelligent system for the fertilizer production process, the obtained fertilizer products fluctuated highly pertaining to the uncertainty of the chemical elements of its raw material like nitrogen, phosphorus, and potassium. Moreover, the chemical measurement of the products itself is not adoptable for the process. Owing to differences in the operatives' experiences and capabilities, the speed of the conveyer belts could not be set systematically. Once the intelligent system for the fertilizer production process was brought into use, the study found that it is efficient enough to be considered for the process of production and the setup of the conveyer belts is likely to be more precise.



(a) (b)

Figure 10. Comparison of error (before and after) for fertilizer where a) is 16-16-8 and b) is 21-7-18

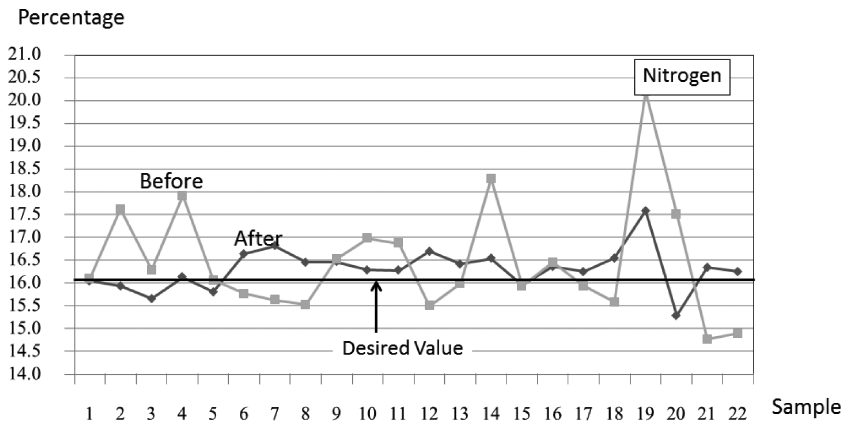


Figure11. Nitrogen before and after implementation for fertilizer 16-16-8

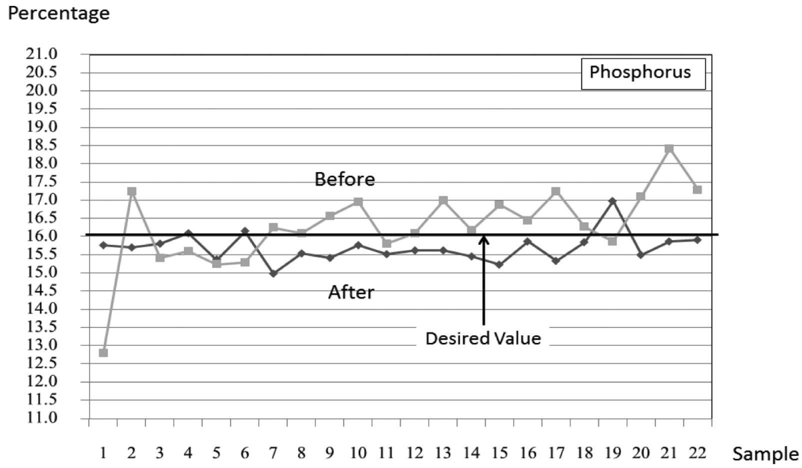


Figure 12. Phosphorus before and after implementation for fertilizer 16-16-8

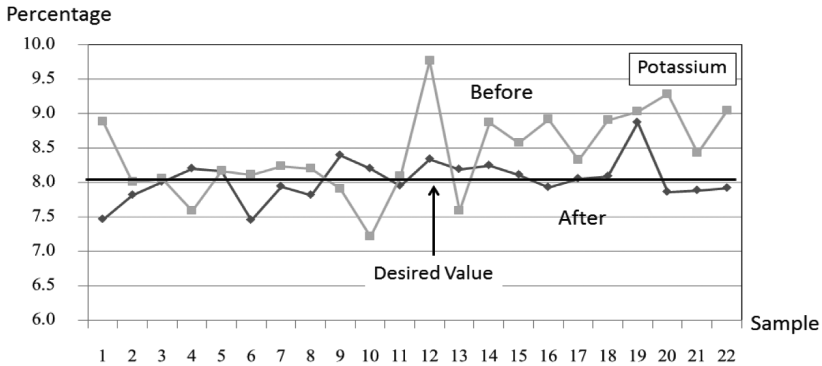


Figure 13. Potassium before and after implementation for fertilizer 16-16-8

Conclusions

This paper proposes an intelligent system for production quality control in a fertilizer plant. The proposed method utilizes an artificial neural network to provide behavior information of the conveyer speed control. This information is acquired and used by the plant's operators. Its output is used to set the initial speed of the raw material belts. Later, if the product error is still high, the FLC will take an action to compensate for this error. The proposed system has achieved a better conveyer speed control compared with the original feeding system that used an operator speed control method. It also shows less fluctuation of the chemical compositon (N-P-K) of the fertilizer product. The fertilizer nutrient results (N, P, and K) demonstrate that this kind of control method is effective in terms of the quality of the fertilizer and the accuracy of the production.

References

Chunying, L. and Xi, W. (2010). Variable-rate fertilization control system based on fuzzy PID control strategy. Proceedings of the International Conference on Electrical and Control Engineering; June 25-27, 2010; Wuhan, China, p. 2511-2514.

Wu, A.I. and Tam, P.K.S. (1999). An adaptive speed control for induction motor drive using fuzzy neural network based on fuzzy hierarchy error approach. Proceedings of the International Conference on Electric Machine and Drive; May 9-12, 1999; Seattle, WA, USA, p. 284-286.

Ying, H. (2000). Fuzzy Control and Modeling Analytical Foundations and Applications. IEEE Press, Atlantic City, NJ, USA, 342p.

Yuan, T.C.C. and Liaw, C.Y. (1994). Design of a neural fuzzy controller. Proceedings of the 20th International Conference on Industrial Electronic Control and Instrumentation; September 5-9, 1994; Bologna, Italy, 1:611-616.

Yusuf, I., Iksan, N., and Herman, N.S. (2010). Weight-feeder control for plastic extruder using fuzzy genetic algorithm. Proceedings of the 2nd Computer and Automation Engineering International Conference; February 26-28, 2010; Singapore, 3:145-149.