Proceedings of the Institute of Acoustics

A PREDICTIVE CONTROL STRATEGY FOR IMPROVING PROCESS CAPABILITY IN ULTRASOUND LEVEL MONITORING

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1. INTRODUCTION

Among the many applications of ultrasound measurement technology, fluid level monitoring in food and drink containers has attracted a great deal of interest from both researchers and the food processing industry. This is partly due to an increasing public environment consciousness and consumer pressure on reducing waste, and partly due to stringent Trading Standard Legislation governing the volume of "fluids" in containers. Faced with the potential risk of legal penalties and adverse publicity, food manufacturers tend to overfill containers in the form of "give-aways". In addition, waste also arises in the form of "throw-aways" as non-conforming underfilled products which end up in rubbish bins.

Unlike the manufacturing industry, food processing companies have lagged behind in the use of high technology measurement instrumentation and process control. It is still a common practice to use bulk measurement techniques in conjunction with open-loop control. While ultrasound measurement technology has the potential to provide accurate on-line measurement, a complementary intelligent process control system is needed in order to benefit fully from the introduction of high technology when attempting to control waste.

Using artificial neural networks for both system identification and parameter estimation, this paper outlines an approach for the design of an adaptive prediction control strategy for improving the control of non-linear systems typified by the filling process. The control efforts are continuously optimised based on the predictions from the neural model. In this manner, artificial neural networks could be trained to provide information on the dynamic model of a filling process.

2. BACKGROUND

Adaptive control, as its name implies, allows the parameters of a model of the process to be adjusted continuously when dealing with the problem of ensuring the output of the process follows the reference signal as closely as possible. Amongst the many adaptive control structures suggested [1], those based on the predictions of the future process outputs (the prediction horizon) have shown to achieve good performance in terms of rapidity, an ability to cope with disturbances and offset cancellations [2,3]. Conventional approach assumes the existence of a process model with unknown parameters in order to make the problem analytically tractable. For simplicity, a linear system model is often used where the system parameters are assumed to remain constant or to vary very slowly over a period of time. Difficulties arise when the operational characteristics of the process (and hence the system parameters) are affected by unforeseen environmental changes, interaction between processes or components deterioration. The non-linearity thus resulted renders the process model inadequate in representing the dynamics of the process.

Extensive analysis is required when attempting to establish an analytical model for a non-linear process, if it is at all possible. Furthermore, the lack of practical and reliable identification techniques for non-linear processes makes it difficult to extend predictive control techniques to non-linear systems [4].

The unique data analysis ability of artificial neural networks has created new opportunities for the development of new control strategy for non-linear processes. Neural networks have been applied successfully to assist with the identification of system parameters [5] and the subsequent development of neural network based predictive control [6,7].

However, most of the work carried out so far has concentrated on off-line system identification. The neural network model of the process thus formed provides information on its dynamic behaviour acquired through training on a sequence of process samples. As the model is predetermined, significant mismatch may arise even after satisfactory training on the collected samples due to unforeseen changes in environmental and/or operational conditions. There is, therefore, a need for model adaptation through on-line training in order to provide on-going improvement of identification accuracy and the ability to track changes in the process dynamics as they occur. Mills et al [8] proposed the use of HS (historic stack) learning algorithm to improve the convergence characteristic of adaptive identification, be it at the expense of bigger computational load at each sample time.

3. The Bottle Filling Problem

Current Trading Standard legislation [9] requires that the volume of liquid in food containers destined for the retail market must contain not less than the amount stated on the label. Compliance of the legal requirements by simply overfilling containers is estimated to cost the UK food industry around £12 million annually in loss revenue.

The variations in the volume of 'fluids' contained in soft drink bottles were investigated by Hull et al [10], in which a number of samples were taken randomly from the production line of a typical soft-drink bottling plant. A summary of the results is reproduced in Table 1. As can be seen, some 72% of the

Number of products examined : 208

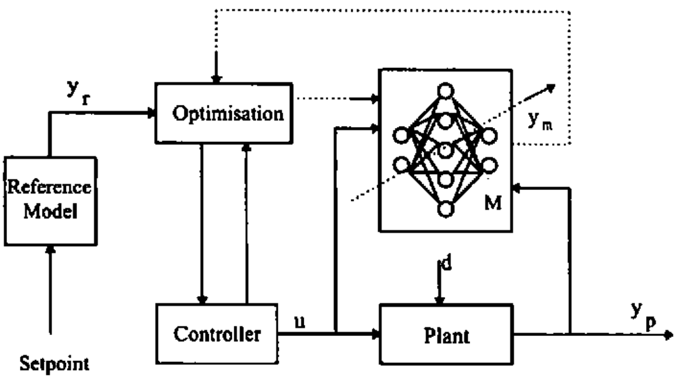
Overfills	No. of items	Underfills	No. of items
Over 3%	12	Less than -2%	5
Between 2 - 3%	63	between 0 to -2%	6
Between 1 - 2%	78		
Between 0 - 1%	44		

Source: Hull et al [10]

Table 1 Summary of the results relating overfill and underfill in two litre bottles finished products contained an overfill of at least 1%, while about 5% of the bottles failed to contain the minimum volume required and would be discarded. The amount of waste (in terms of overfill and non-conformance) reflects the inadequacy of both of the methods used for fluid level measurement and the control strategy adopted. Replacement of the bulk measurement techniques by the ultrasound monitoring offers the potential of an accurate on-line feedback, but the benefits of using highly accurate measurement technology may not be fully realised unless a complementary intelligent process control system is also developed for the bottle filling system. As bottle filling is a non-linear process where the system characteristics may change during a filling operation, a neural network based adaptive prediction control strategy is proposed for this application.

4. A Neural Network Based Control Strategy

The proposed non-linear control strategy for the filling process is shown in Figure 1. The structure is similar to that of a conventional adaptive control except that a neural network acts as an adaptive/ intelligent plant model which provides predictions of the plant output.



Key

u : plant input signal
d : disturbance signal
M : neural model
y_r : reference signal
y_m : network predictions
y_p : plant output

Figure 1 A neural network based control structure

The plant is assumed to be adequately described by the following generalised model for non-linear systems [5]. The non-linear mapping function f takes the form of a neural network, k is the present discrete time step and u is the plant input signal.

$$y_p(k) = f[y_p(k-1), y_p(k-2), y_p(k-3), u(k-1), u(k-2)] ;$$

where $$f[x_1, x_2, x_3, x_4, x_5] = \frac{x_1 x_2 x_3 x_5 (x_3 - 1) + x_4}{1 + x_3^2 + x_2^2}$$

$$x_1 = y_p(k-1), x_2 = y_p(k-2), x_3 = y_p(k-3), x_4 = u(k-1), x_5 = u(k-2)$$

The parametric values for x_1, x_2, x_3, x_4, x_5 are the same as those used in [5].

Unlike the conventional approach, identification of the system is to be carried out by a back-propagation neural network. Where applicable, initial training of the network is accomplished by subjecting it to random number input between -1 and +1 until satisfactory convergence has been achieved. The neural network model thus obtained will enable the plant output y_p to be predicted based on the past values of output and process input. Subsequent updating of the weights in the neural model is carried out within the control structure by means of on-line learning.

The predictions from the neural model enable the control efforts to be optimised using the technique proposed by Powell [11] for non-linear systems. A schematic diagram of the optimisation procedure is shown in Figure 2. It should be noted that the same neural network has been used for the following three tasks: system identification, prediction of the plant output and facilitating the optimisation of control actions.

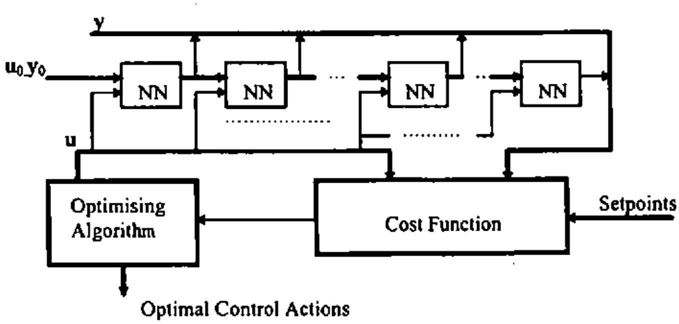


Figure 2 Control efforts optimisation based on neural network predictions

5. The Results

By means of computer simulations, the proposed prediction control strategy has been tested using three sets of excitation signals: sine wave, square wave and multi-steps. The latter is particularly important as all industrial plants are subjected to load-disturbances which tend to be in the form of random-steps at random times in the deterministic case or of Brownian motion in stochastic systems. Two identical back propagation neural networks with the configuration of 5-20-10-1 are used for the study : one to be given some initial training using random numbers between -1 and +1, the other to be trained entirely on-line.

5.1 Identification of Systems

Characterisation and identification of a system to be controlled are fundamental to the system theory. The problem of identification consists of developing a suitable mathematical model expressed in terms of system parameters of unknown values. Determination of these values by suitable means is then carried out and the parameters of the model are adjusted to optimise a performance function based on the error between the plant and the model output. Identification of linear systems using the conventional methods is reasonably straight forward, but the opposite is true for many industrial processes where non-linear functions (mostly unknown) pre-dominate.

If an assumption is made that the weight matrix of a neural network exists in the proposed control structure (Figure 1), the identification procedure involves adjusting the weights of the neural network until both the plant and the neural model have the same output for any specified input. The neural network is learned by cycling through a sequence of pattern sets, updating the weights at each presentation until learning is complete.

Figures 3 and 4 show the tracking ability of the neural network if the control strategy is used purely for identification purpose. The network was given initial off-line training on random number input between -1 and 1, and convergence was achieved after about 50,000 steps. While the network identifies random step input with good accuracy, it exhibits discrepancies when tracking the negative part of a sine function. The control strategy is ready for testing once the integrity of the system identification process has been established, including the knowledge of the minimum iterative steps needed for initial off-line training.

5.2 Non-Adaptive Prediction Control

The proposed control structure permits the use of non-adaptive neural model when implementing prediction control. This means that the weights of the neural network would not alter once it has been fully trained off-line. The predictive and control horizons are set at two steps ahead and the optimisation procedure remains active throughout. Figure 5 shows the response of the non-adaptive control system when subjected to a train of pulses as the reference signal. The control system produces a good response time (about 16 discrete time steps) coupled with an offset of the order of 5% . A larger discrepancy can be seen when it deals with a sine input function. If non-adaptive control is to be used, the problem of offset can be remedied by incorporating a measure of integral control in the structure, even though this approach may not be the efficient way of going about it.

5.3 Adaptive Prediction Control

By utilising the unique learning ability of a neural network, the neural model within the control structure could be made adaptive in order to follow the reference signal as closely as possible. Figures 7 and 8 show the responses of the control system to two sets of reference input signals when adaptive neural model has been activated. In both cases, "pre-operational" off-line training using random number input was given to the network until convergence before switching it to on-line control. The amount of "pre-operational" training needed for the irregular steps and the sine function were 480 and 100 time steps respectively. The implementation of adaptive control has effectively removed the offset while maintaining a good response time. The improvement is most profound in the case of the sine function input.

The results presented so far are for control systems where the neural networks have been given prior training. It begs the question "How would the control strategy perform if no prior training is given to the network when on-line control is activated ? The answer to the question is provided by the results shown in Figures 9 and 10. In both cases, the neural model was expected to learn on-line as the control strategy was being implemented. Encouraging results were obtained with the system response stabilised after about 300 time steps for the square wave input and 250 steps for the sine function.

6. Concluding Remarks

The process of identifying the model of a plant to be controlled has always been a challenging task. The problem is compounded if the plant characteristics are susceptible to changes brought about by environmental variations and the interactions between processes. The non-linearity thus formed greatly reduces the effectiveness of a pre-determined plant model for control purposes. An adaptive model would have been an ideal solution had it not been for the fact that, for conventional approach, the computational resources required for its implementation would be prohibitive for most cases.

With their unique data analysis ability, artificial neural networks appear to offer a practical alternative to the conventional methods of adaptive model identification within a control framework. The results presented in this study show the viability of using a neural network as a pseudo plant model to facilitate the development of an adaptive control strategy for non-linear processes. For the bottle filling operation which is a non-linear process, close integration of ultrasound monitoring technology with neural network based adaptive control offers potentially a winning combination.

7. References

[1] Isermann R., Lachmann K. and Matko D. Adaptive Control Systems, Prentice Hall, 1992.

[2] Clarke D.W., Moktad C. and Tuffs P.S. Generalised Predictive Control - Part I, The Basic Algorithm, Automatica, Vol 23 (2), 1987.

[3] Kinnaert M. Adaptive Generalised Predictive Controller for MIMO Systems, International Journal of Control, Vol 50 (1), 1989.

[4] Bittani S. and Piroddi L. GMV Technique for Nonlinear Control with Neural Networks, IEE Proceedings-D, Vol 141 (2), 1994.

[5] Narendra K.S. and Parthasarathly K. Identification and Control of Dynamic Systems Using Neural Network, IEEE Trans. on Neural Networks, Vol.1 (1), 1990.

[6] Hunt K.J. and Sharbaro D. Neural Networks for Nonlinear Internal Model Control, IEE Proceedings-D, Vol 138 (5), 1991.

[7] Willis M.J., Montague G.A., Massimo C.D., Tham M.T. and Morris A.J. Artificial Neural Networks in Process Estimation and Control , Automatica, Vol 28 (6), 1992.

[8] Mills P.M., Zomaya A.Y. and Tade M.O. Adaptive Model-based Control Using Neural Network, International Journal of Control, Vol 60 (6), 1994.

[9] Weights and Measures Act, Material from the Trading Standards Service, 1972.

[10] Hull J.B., Henthorn K.S. and Muumbo A.M. Controlling Waste in the Food Processing Industry using Ultrasound Monitoring Technology, 2nd international Conference on Advances in Materials and Processing Technologies (AMPT95), Dublin, 1995.

[11] Powell, M.J.D. An efficient method for finding the minimum of a function of several variables without calculating the derivatives. Computing Journal (7), 1964.

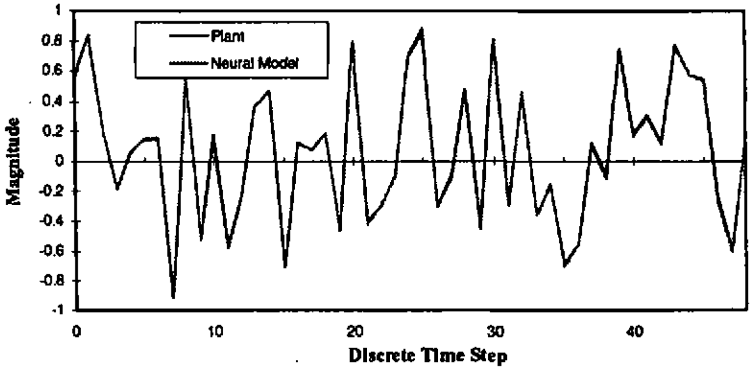


Fig 3.Verification of the neural model using random inputs

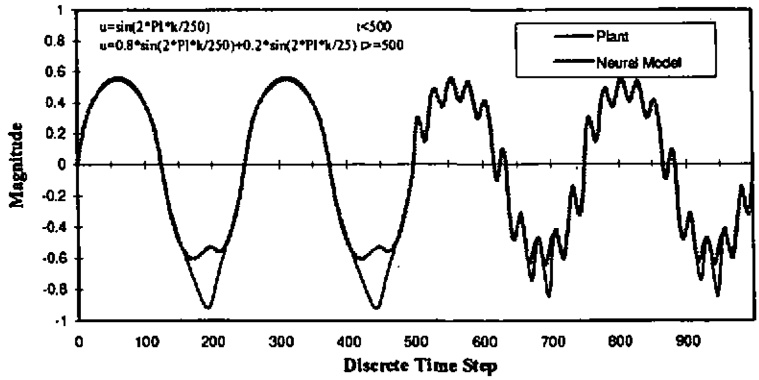


Fig 4. Verification of the neural network model using sine functions

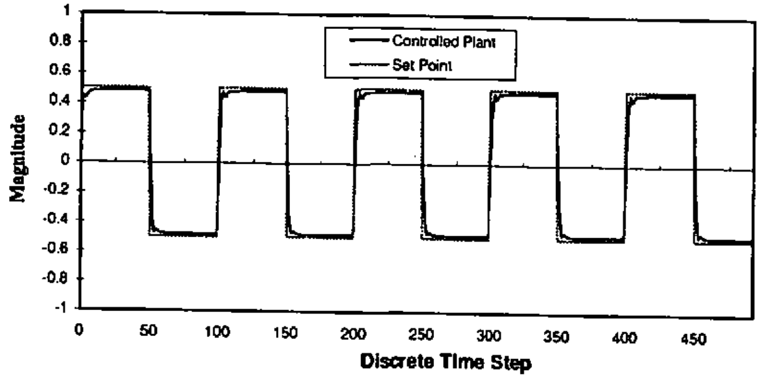


Fig 5.Plant outputs with non-adaptive control

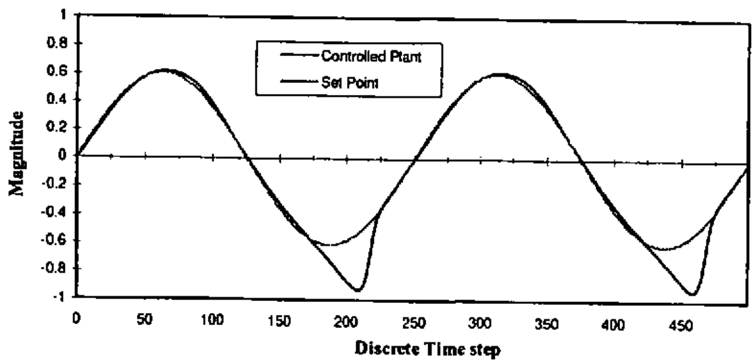


Fig 6.Plant outputs with non-adaptive control

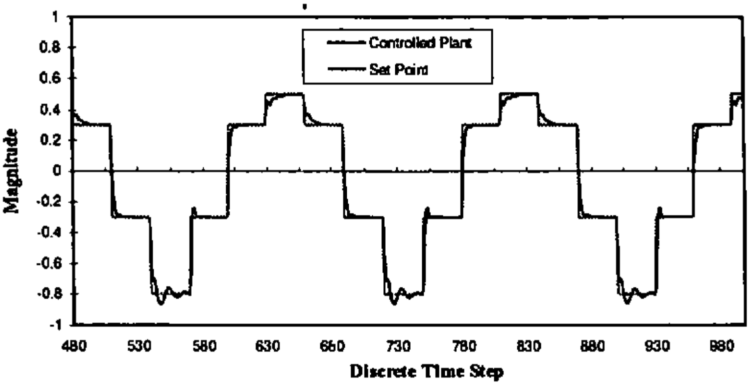


Fig 7.Plant outputs with adaptive control (with off-line training)

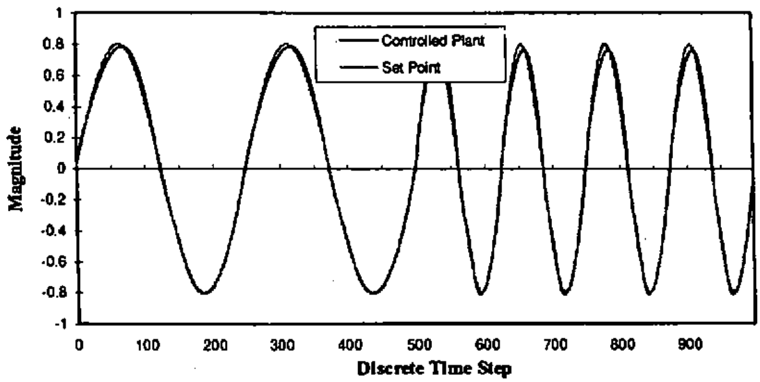


Fig 8.Plant outputs with adaptive control (with off-line training)

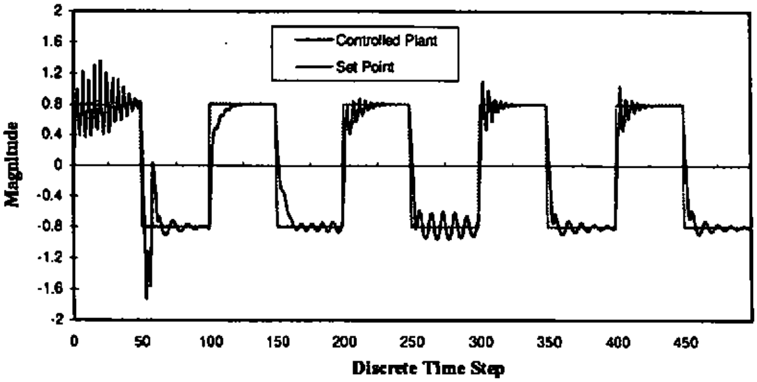


Fig 9.Plant outputs with adaptive control (without prior training)

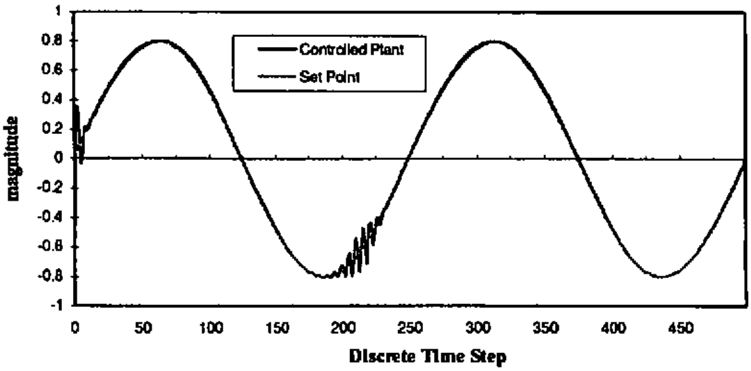


Fig 10.Plant outputs with adaptive control (without prior training)