Application of Neuro-Fuzzy for Improving Volume Control in Water Canning Industry

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***Abstract*—The computation minimization which is associated with neurofuzzy models and controllers may be installed in industrial programmable Logic controllers (PLC). The implementation of thermal sterilization is both model and control in order to validate the pilot plant of water canned industry. Volume control in beverage manufacturing companies requires that a certain measured volume be filled into specific container sizes to conform to already predetermined standard to ensure competitiveness in the industry. However, most industry does not have accurate and reliable monitoring mechanism capable of sensing when the canned bottles are not properly filled. This operational failure can be overcome by designing a model that will monitor and control the filling process thereby improving volume control in water canning industry using feedback Neuro-fuzzy control. MATLAB Software was used to carry out simulations to develop volume control in water canning industry with aims of improving operational mechanism of industry. The result of the research revealed the empirical data collected in Rancor Nig. Ltd., Enugu, Nigeria and feedback Neurofuzzy. This ANN model can then be trained with values generated from an already existing mathematical model to be able to monitor and control the filling of the cans. The result showed that volume control in water canning industry with and without feedback Neuro-fuzzy were 63cl and 50cl respectively. The volume increased by 13cl. With these results, it shows that using feedback Neuro-fuzzy gives a better result in terms of filling to the required volume of the bottle than when feedback Neuro-fuzzy is not used.**

***Index Terms*—Feedback Neuro-Fuzzy; Improving; Control; Training.**

I. Introduction

The resent approach to predictive control is observed in a well-established technology which is applying many fields, especially in industrial processes. Its efficiency has been tested over the last few years. Generally, most applications of predictive control are based on linear models, which gives good results especially if they work around a duty point [5]. However, the region applications of or the degree of "non-linearity" always reduce the linear model system prediction capacities which leads to a poor control quality. Hence, Non Linear Model Predictive control (NMPC) is the best option. Therefore, the Application number of NMPC is limited due to tremendous potential. Nonlinear dynamic has highest possibility advantages over MPC.

Another disadvantage is that the optimizer solution in non-linear Predictive Control is a non-convex problem and a large computational effort may be required to obtain the solution. This is especially relevant when dealing with real time tasks due to the low computational capabilities of most platforms for industrial control based on PLCs (Programmable Logic Controllers).

Fuzzy models allow exert solutions of the optimization (without restrictions) with a low computational cost. It should be remarked that an NMPC procedure based on Fuzzy models could be implemented on small platforms like PLCs. In this paper, neurofuzzy modeling has been used having a Fuzzy Inference System (FIS) as a model for NMPC. Fuzzy control has been applied successfully in many industrial processes [8]. It has required a special part of the IEC 1131 [7] standard, which is about industrial PLC. Many groups have been involved in this part, leading to IEC 1131-7 [6]. The norm establishes, in addition, a set of optional parameters for them. Within the scope of the norm, programmers have an easy way to implement NMPC.

The sterilization of solid food in steam retorts has been chosen as a bench- mark because this system presents a highly nonlinear behaviour. In addition, the operation needs to be guided by the achievement of strict requirements on microorganisms' thermal destruction while maintaining the product under acceptable organoleptic specifications. Such goals must be attained despite a number of undesirable disturbances acting within the process like sudden steam temperature shut down situations due to boiler overload (excessive steam demand from different retorts). The process is also subject to a considerable degree of parameter uncertainties and to some extent also to a lack of accurate dynamic models (structural uncertainty): many simplifications like spatial homogeneity or isotropy assumptions are considered in order to obtain tractable models. All these issues make the plant be a good test bed for the illustration of the capabilities of the nonlinear predictive control strategies based on fuzzy models quoted before. Two different techniques have been developed using neurofuzzy models with Generalized Predictive Control (GPC) [4] and applied to control the thermal sterilization process in steam retorts. A Proportional-Integral-Derivative PID controller is a commonly used feedback controller which control industrial systems. The controller parameters are chosen through a certain optimal method. Since the chosen parameters are fixed, the conventional PID controller cannot always provide satisfying performances and optimal control of the system or

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stability of the system is not guaranteed. Control of variable area tanks is a challenging cum necessary task in process industries as the variable area contributes the major part of the non - linearity component. Conventional PID controller with fixed PID parameters will not meet out the control demands of such processes. Spherical tank is one such process, needs fixed PI controller parameters to be altered, even for a slight change in operating point of the process. Hence a scheduler is proposed to adjust KC and TI values of the PI controller with respect to changes in the operating level ' h' of the tank.

Fuzzy logic is used to convert heuristic control rules stated by a human operator into an automatic control strategy. [2] proposed a general neural- network model for fuzzy logic control and decision systems. Their connectionist model combined the idea of fuzzy logic controller and neural network structure and learning abilities into an integrated neural-network based fuzzy logic control and decision system called Adaptive Neural Fuzzy Inference System (ANFIS). The proposed work is an attempt to incorporate ANFIS based scheduler to adjust the KC and TI values of feedback PI controller in maintaining the desired level of spherical tank process.

II. Fuzzy Modeling

The Application require mathematical model which corresponds to the actual inputs to outputs, where the aims is to approximate a function y=f(x) with input x= (x_1,x_2---x_n).

If x_1 is C_{1j} and x_2 is c_{2j}; So, x_n is c_{nj}. Then y_j is D_j, where C_{ij} is a membership function of the input x_i and c_j with ouput D_j. The defuzzifier is:

$$y = \frac{\int\limits_{\alpha} \mu(y).ydy}{\int\limits_{\alpha} \mu(y).dy} \tag{1}$$

where:

$$\mu(y) = \cup\left[\min\left(\prod_{i=1}^{n} \mu_{ij(x)}\right)\right], V_j(y)$$

$V_{i(y)}$ represent the degree of membership of the output y_j to C_j

$\mu_{ij}(x)$ represent degree of membership of input x_i to the fuzzy set c_{ij}.

III. Neurofuzzy Models

Neuro fuzzy models [12] have been applied successfully in non-linear model based techniques [10]. This provide optimization model for the parameter in the fuzzy system which gives the best fits [13]. These models may be formulated as an Adaptive Neuro-Fuzzy Inference System (ANFIS) [9]. ANFIS is presented as an example with N input variables, one output variable and five layers. The first layer is composed of membership functions A_{uij}, defined by the membership degree.

$$\mu A_{uij} : u_i \in R \longrightarrow \mu A_{uij}(u_i) \in R \tag{2}$$

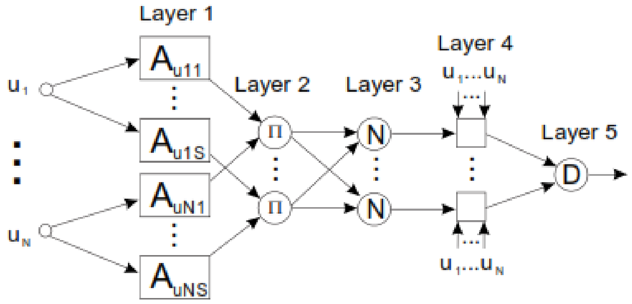

Fig. 1. Fuzzy Neural Network [9]

The output of each node i is μA_{uij} ($_{ui}$), the membership degree of u_i. For the definition of these membership functions, some standard types are used. In this work, gaussian membership functions are used. The second layer has nodes labelled with Π which implement fuzzy inference machine. For example, if logical operation AND is carried out by multiplication, the output of each node j of this layer is:

$$\omega_j = \mu A_{u1j}(u_1)\cdot\mu A_{u2j}(u_2)\cdot\ldots\cdot\mu A_{uN\,j}(u_N) \tag{3}$$

$$\bar{W}_i = \frac{w_i}{\sum_{i=1}^{N} w_i} \tag{4}$$

The fourth layer has adaptive nodes:

$$\bar{W}_i\ f_i = w_i(pl_i u_i + - \bar{-} + pN_i uN + r_i)$$

Finally, the fifth layer is the defuzzyfication node: for TS systems, the output will be:

$$\sum_{i=1}^{N} \bar{w}_i f_i = \frac{\sum_{i=1}^{N} w_i f_i}{\sum_{i=1}^{N} w_i} \tag{5}$$

Fuzzy Neural Networks (FNN) combine the capability of uncertainty handling in information with learning skills [9], [11]. Recurrent Fuzzy Neural Networks (RFNN) have demonstrated to be better at getting all the dynamics of nonlinear systems. They are systems which have the same advantages as recurrent neural networks [3],[1]. RFNN are also named *Fuzzy Dynamical Systems* and extend the application domain of FNN to temporal problems. Feedback allows the capture of dynamics and change. In the neurofuzzy model proposed by Takagi-Sugeno(TS), the structure of antecedent describes fuzzy regions in the input space, and the one of consequent presents non-fuzzy functions of the model inputs. If recurrent functions with NARMAX structure (*Non-linear Auto Regressive Moving Average with eXogenous input)* of the kind:

$$\hat{y}(k+1) = f(y(k),\ \ldots, y(k-m),\ u(k),\ \ldots, u(k-n))$$

are used, being u, y for each rule the inputs and outputs of the system respectively, the system may be described by the following way:

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IF $x_{1(k)}$ is F_{1j}, ..., and $x_{n(k)}$ is F_{nj},

THEN: $y_{j(k)} = a_j(z^{-1})y(k-1) + b_j(z^{-1})u(k-d) + c_j$

With $a_j(z^{-1}) = a_{1j} + a_{2j}z^{-1} + ... + a_{nj}z^{-(ny-1)}$ and $b_j(z^{-1}) = b_{0j} + b_{1j}z^{-1} + b_{2j}z^{-2} + ... + b_{nj}z^{-nu}$ and where $X_{u(k)} = [x_{1(k)} x_{2(k)}...x_{n(k)}{}^{y}]^T$ is the input vector of the neurofuzzy system in the instant k, Fij is the fuzzy set respective to xi(k) on the rule j, yj (k) is the output of the model respective to the operating region associated to the rule, d is the dead time and cj is a constant term. If μij (k) is the membership degree of xj (k) in the fuzzy set Fij and the number of implications or rules is L, the RFNN complete model is possibly described by:

$$y(k) = \sum_{j=1}^{L} w_j(k)[a_j(z^{-1})y(k-1) + b_j(z^{-1})u(k-d)] + \xi(k)$$

Where $w_j(k) = \dfrac{\bar{\mu}_j(k)}{\sum_{j=1}^{L}\bar{\mu}(k)}$, $\bar{\mu}_j(k) = \prod_{i=1}^{n}\mu_{ij}(k)$ and $\xi(k) = \sum_{j=1}^{L} w_j(k)$.

IV. Materials and Method

This research was carried out using a well-known bottled water manufacturing company, Rancor Nig. Ltd., Enugu, Nigeria. The following parametric values were got from the operational outlet of Rancor Nig. Ltd Enugu. The mathematical model was formulated from the experimental data collected. The designed model and analysis was performing in MATLAB/Simulink in order to monitor and control the filling process of canny bottles. The Feedback was train in ANN controller optical sensor.

TABLE I: Bottle Container Measurements

Radius of a bottle	2cm
Height of a bottle	5cm
π	3.142
Volume	

To find the volume of a cylindrical bottle which is the mathematical model for improving volume control in water canning industry using feedback ANN control

$V = \pi r^2 h$ (1)

V = Volume of cylindrical water bottle canning

r = Radius of the cylindrical water bottle canning

h = height of cylindrical water bottle canning

Then, the volume of cylindrical water bottle canning to be used for the process becomes

$V = 3.142 \times 2^2 \times 5$

$V = 3.142 \times 4 \times 5$

$V = 62.8\ cm^3$

$62.84cm^3$ is the ideal volume of the water bottle canning for the process. On the other hand, if the volume is increased by adjusting the height of the cylindrical water bottle there will be waste of water.

To adjust the height to 6cm

Then, recall (1) and substitute 13 for h and 5 for r

Recall $V = 3.142r^2h$ (1)

$V = 3.142 \times 2^2 \times 6$

$V = 75.4cm^3$

$75.4\ cm^3$ is the volume of water when the height of the cylindrical water bottle canning is used. This means that quantity of water wasted in the manufacturing process is $(75.4 - 62.8)\ Cm^3 = 12.56cm^3$. This means that the quantity of water wasted in the process is $12.6Cm^3$.

Similarly, adjusting the height of the cylindrical bottle to 4.5cm, then, the volume of the water becomes

$V = 3.142 \times 2^2 \times 4.5$

$V = 56.6cm^3$

It means that the volume of the cylindrical water bottle is short by $(75.4 - 56.6)\ Cm^3 = 18.8\ Cm^3$.

The primary aim of the design is to make sure the canny water is $63cm^3$. This standard volume will be used to design a fuzzy rule.

V. Discussion of Result

Fig. 2 shows the trained values gotten from the mathematical model to monitor and control the filling of the cans. Fig. 2 shows 63 neurons which represents 63 volume of the canny water. It is trained in the manner that the volume of canny water will be $63cm^3$. On the other hand, if the volume is above or below $63cm^3$ it will show red light indicator instructing the operator to remove it.

Fig. 3 shows designed model for improving volume control in water canning industry without using feedback ANN controller. The filled canny level is $62.5cm^3$ when conventional method is applied.

Fig. 4 shows improving volume control in water canning industry without using feedback ANN controller. Fig. 6 shows that as a result of some disturbances the coordination of the volume of canny water to time rises a (80, 1) and stabilizes to get the actual volume at a coordination of (61.5, 4) to (61.5, 10).

Fig. 5 shows improving volume control in water canning industry using feedback ANN controller. The result shows that as a result of some disturbances the coordination of the volume of canny water to time rises a (83, 1) and stabilizes to get the actual volume at a coordination of (63, 4) to (63, 10).

Fig. 6 shows comparing improving volume control in water canning industry with and without using feedback ANN controller. Its shows that the volume of water canning when feedback ANN is not used is $61.5cm^3$while the volume of water canning when feedback controller is used is $63cm^3$. With this result it shows that there is an improvement of $1.5cm^3$ volume of water when feedback ANN is used.

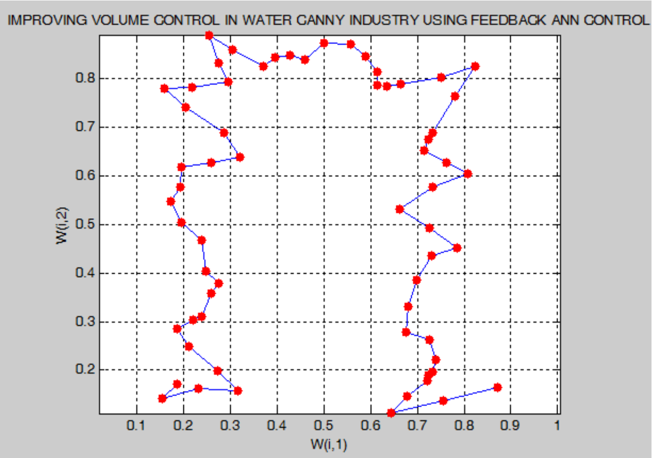

Fig. 2. Trained values got from the mathematical model to monitor and control the filling of the cans.

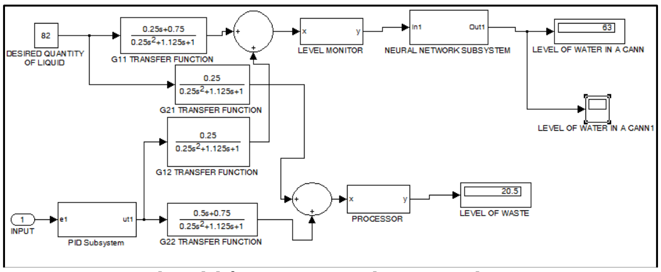

Fig. 3. Designed model for improving volume control in water canning industry using feedback ANN controller.

TABLE II: IMPROVING VOLUME CONTROL IN WATER CANNING INDUSTRY WITHOUT USING FEEDBACK ANN CONTROLLER

VOLUME OF CANNY WATER WITHOUT FEEDBACK ANN (CM^3)	TIME (S)
0	0
80	1
55	2
63	3
61.5	4
61.5	5
61.5	6
61.5	7
61.5	8
61.5	9
61.5	10

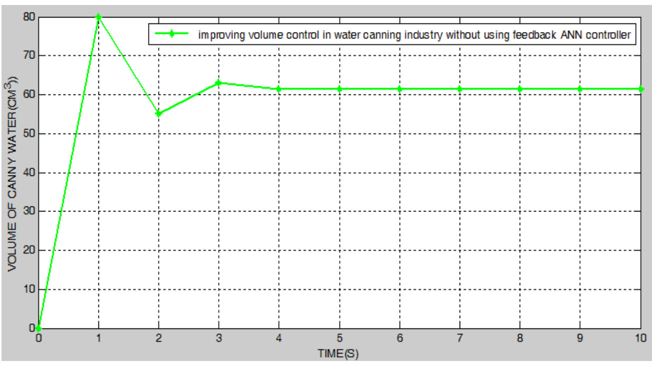

Fig. 4. Improving volume control in water canning industry without using feedback ANN controller

TABLE III: IMPROVING VOLUME CONTROL IN WATER CANNING INDUSTRY USING FEEDBACK ANN CONTROLLER

VOLUME OF CANNY WATER USING FEEDBACK ANN (CM^3)	TIME (S)
0	0
83	1
57	2
65	3
63	4
63	5
63	6
63	7
63	8
63	9
63	10

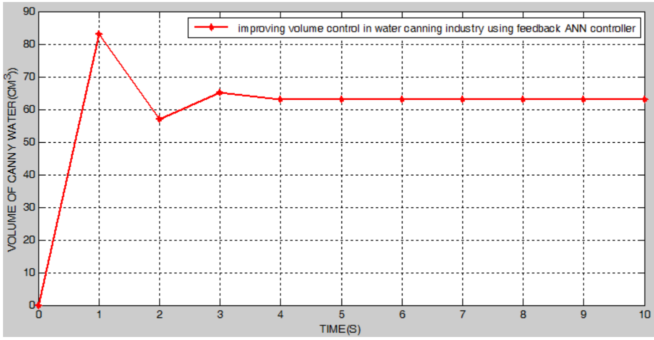

Fig. 5. Improving volume control in water canning industry using feedback ANN controller

TABLE IV: COMPARING IMPROVING VOLUME CONTROL IN WATER CANNING INDUSTRY WITH AND WITHOUT USING FEEDBACK ANN CONTROLLER

VOLUME OF CANNY WATER WITHOUT FEEDBACK ANN (CM^3)	VOLUME OF CANNY WATER USING FEEDBACK ANN (CM^3)	TIME (S)
0	0	0
80	83	1
55	57	2
63	65	3
61.5	63	4
61.5	63	5
61.5	63	6
61.5	63	7
61.5	63	8
61.5	63	9
61.5	63	10

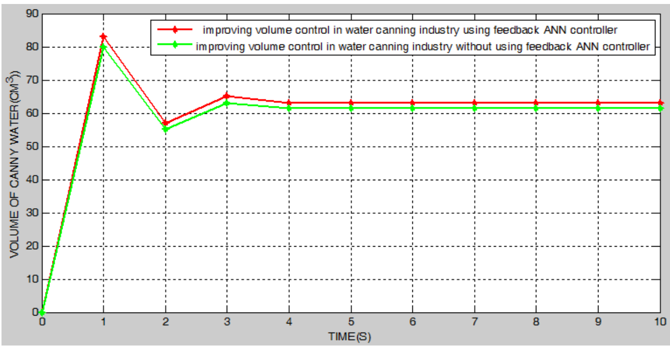

Fig. 6. Comparing improving volume control in water canning industry with and without using feedback ANN controller

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VI. Conclusion

This operational failure of canning industry can be overcome by designing a model that will monitor and control the filling process thereby improving volume control in water canning industry using feedback Neuro-fuzzy control. MATLAB Software was used to carry out simulations to develop volume control in water canning industry with aims of improving operational mechanism of industry. The research paper revealed the empirical data collected in Rancor Nig. Ltd., Enugu, Nigeria when feedback Neuro-fuzzy is used. Therefore, the research characterized the network, designing a mathematical model from the empirical data collected, training the values gotten from the mathematical model to monitor and control the filling of the cans, designing a model that will monitor and control the filling process, designing a model for improving volume control in water canning industry using feedback ANN control and comparing the result achieved with the conventional one. The result showed that volume control in water canning industry with and without feedback Neuro-fuzzy were 63cl and 50cl respectively. The volume increased by 13cl, which is 11.5% increase after feedback Neuro-fuzzy. With these results, it shows that using feedback Neuro-fuzzy gives a better result in terms of filling to the required volume of the bottle than when feedback Neuro-fuzzy is not used.

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