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Full Length Research Paper

Online Quantitative feedback theory (QFT) -based self-tuning controller for grain drying process

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This paper presents a development of QFT-based self-tuning controller for a conveyor belt type grain dryer plant. Grain drying process is complex due to long time delay, presence of disturbances and plant uncertainty. QFT technique potentially has excellent solution towards this problem due to its well known capability to achieve robust performance regardless parameters variation and disturbances. The mathematical model of the grain dryer plant is obtained using system identification based on real-time input/output data. A fixed robust controller could be designed using QFT technique; nevertheless the uncertainty range must be defined. However, in grain drying process, the parameters' variations are unpredictable and may exceed the defined uncertainty ranges. Therefore, adaptive control with integrated Quantitative Feedback Theory (QFT) constraints is proposed to adapt larger parameters variation. Improved results are obtained by using the proposed method as compared to standard QFT procedure in terms of smaller percentage overshoot and shorter settling time when dealing with larger uncertainty range. In addition, the design methodology of the proposed controller design (loop shaping) was improved such that the dependency on human skills was removed and the controller design was done online.

Key words: Self-tuning, quantitative feedback theory, adaptive, grain drying, system identification.

INTRODUCTION

Grain drying is a very important process in post-harvest agricultural process. Grain needs to be dried to specific moisture content before it is safe for storage. The drying process is very complex and difficult to control due to long delay, highly non linear behaviour and presence of disturbances. During the drying process, the interaction between temperature and humidity of both drying air and grain may vary both in time and place which are very complex and highly non linear. A good grain dryer control system should meet the control objectives; stability of the system, accuracy of the product close to desired moisture content and robustness of the controller towards any disturbances such as environmental changes and hardware wear and tear (Liu and Bakker-Arkema, 2001). There are several methods that have been implemented to control grain dryer plant. Some distinctive examples are Nybrant (1988) who developed a model for cross flow grain dryer for use in the development of adaptive control system, Liu and Bakker Arkema (2001) who developed and tested model predictive control for maize cross flow dryer, Whitfield (1988) who developed and tested his Proportional Integral (PI) algorithm on mixed flow dryer and Atthajariyakul and Leephakpreeda (2006) who implemented new modern fuzzy logic technology to

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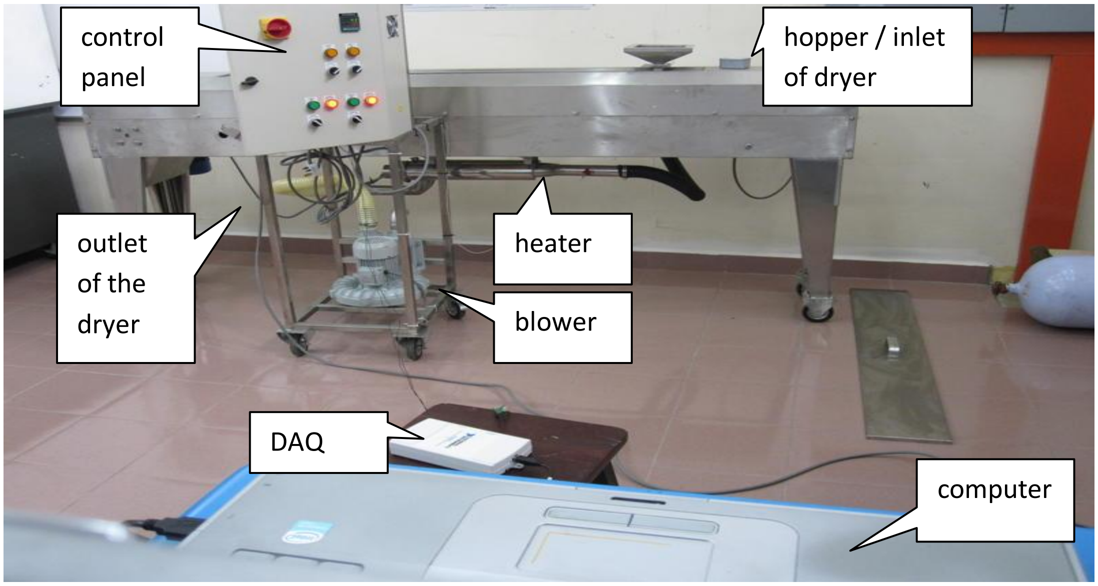

Figure 1. Conveyor belt type grain dryer in Faculty of Engineering, Universiti Putra Malaysia.

control fluidised bed paddy dryer.

Parameters uncertainty which may come from modelling and hardware manufacturing tolerance adds to the difficulty in designing efficient grain drying control system. Quantitative Feedback Theory (QFT) is a robust controller technique that deals with plant uncertainty and designed based on robust specifications. QFT technique has been proven to control many industrial applications; however, the application of QFT to grain dryer plant is practically new. Some successful examples of QFT applications are in flight control system, marine auto-pilot, power converter, pneumatic servo actuator and robotic (Noor, et al., 2011; Altowati, 2007; Desanj and Grimble, 1998; Sheldon and Rasmussen, 1994; Chang et al., 1991). Shams et al. (2010) compared the performance of QFT with traditional PI controller and found the effectiveness of the QFT-based controller over the traditional method. Their study was based on load frequency control. Hemmati et al. (2010) provides comparisons between QFT, genetic algorithm, and fuzzy logic on his power system stabilizer (PSS) study. His findings showed that QFT based PSS provides among the best performance compared to other methods and conventional PSS. However, the QFT-based controller performance is only guaranteed for a certain uncertainty range defined by the designer. In grain dyer process, the uncertainty might goes beyond the specified range. Therefore, adaptive control is important, adaptive can cope with larger uncertainty range. Due to the fact that grain drying process needs both robust and adaptive control, the objective of this research is determined. The objective of this research is to design an online self-tuning controller for a grain dryer plant which is robust and capable to adapt wider parameters variation regardless presence of disturbances. The initial controller is determined by using standard QFT procedures. Based on the structure of the controller, the adaptive controller is designed. Based on minimisation of the system error function, Recursive Least Square (RLS) method is used to identify the plant parameters according to plant changes. RLS provides fast convergence in parameters estimation (Wang and Feng, 2009). The controller's parameters are determined from the algebraic method which has been integrated with QFT constraints. From the extensive simulation results, the proposed controller is found to be efficiently control the grain drying process regardless presence of disturbances as well as parameters variation. The online QFT-based self-tuning controller produced more desirable response than standard QFT-based controller in the case of larger parameters variation as well as, improved the controller design methodology.

MATERIALS AND METHODS

This paper is focused on the control design methodology for a conveyor belt type grain dryer. More discussion on controller's design will be found in this section. However, brief discussion on the grain dryer plant and the methods on obtaining the mathematical model of the grain dryer will be presented.

Grain dryer plant

The grain dryer plant under study is a laboratory scale continuous flow conveyor belt type grain dryer with dimension: 2300 mm (L) × 350 mm (W) × 800 mm (H). Experiment was conducted on the grain dryer for data collection. Paddy grain was used in this experiment. As shown in Figure 1, the grain dryer was connected to a computer

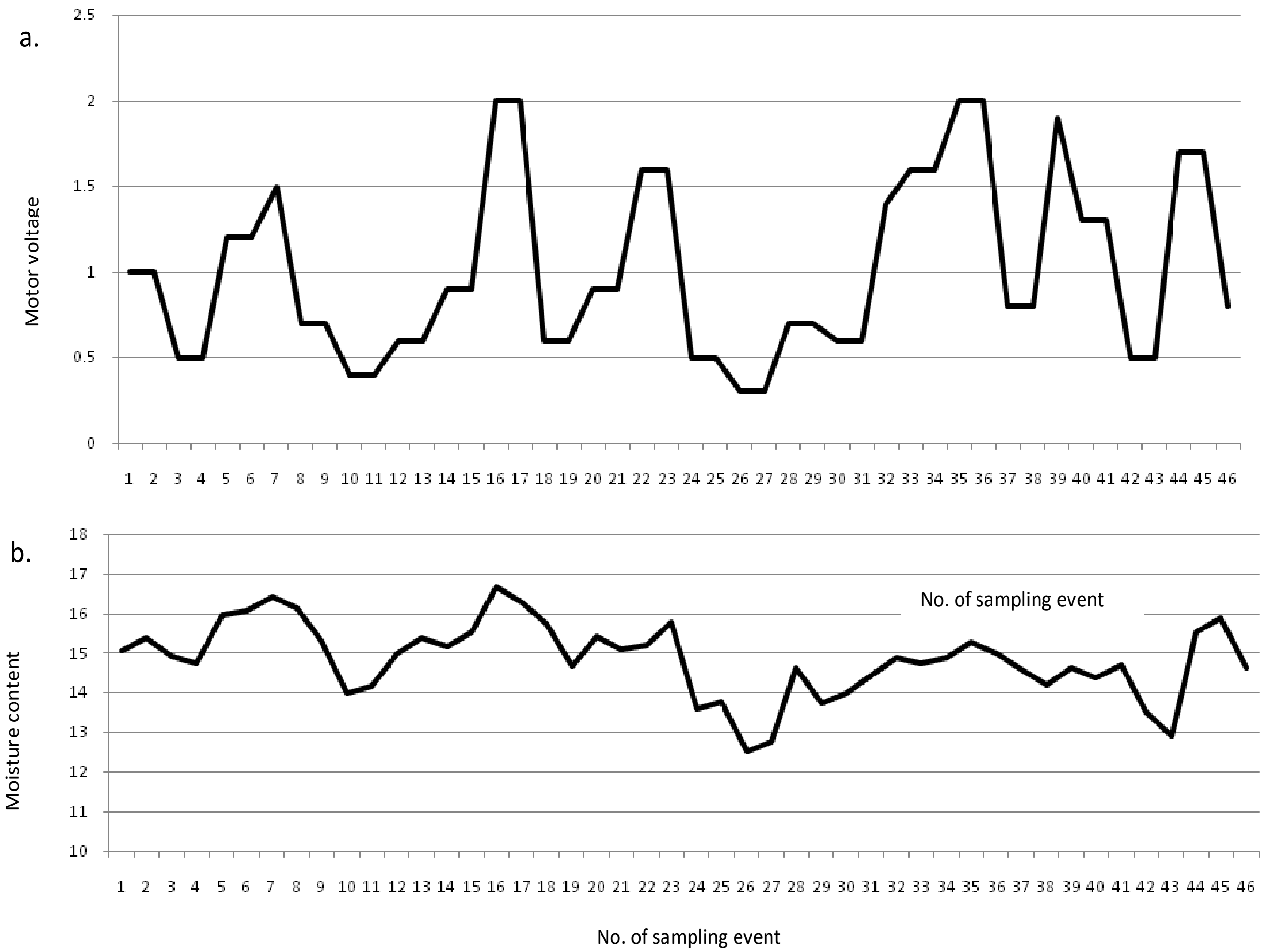

Figure 2. Input and output data collection a) voltage supplied to the motor (V) b) grain moisture content collected at the output (% w.b).

via National Instrument Analogue Output Data Acquisition System (DAQ), particularly NI USB-6211 DAQ. Offline moisture analyser (Precisa XM 120) was used to determine the moisture content of the grain. Wet grain of about 17% w.b. moisture content was spread evenly at the inlet of the dryer. The conveyor belt moved the wet grain towards the outlet while the blower blew the hot air supplied by the heater. By manipulating the speed of the motor that rotates the conveyor belt (varying the residence time), the respective grain moisture content was measured. From the control system point of view, the input of the system is the voltage supplied to the motor (set between 0.3 to 2 V) and the output is the grain moisture content collected at the end of the dryer. The input and output data is represented in Figure 2.

The grain dryer model

The input and output data has been used to obtain the mathematical model of the grain dryer, using System Identification (SI). Matlab System Identification Toolbox (MSIT) has been used to simplify the mathematical calculations (Ljung, 2008). Linear process model has been chosen to represent the grain dryer plant. In order to apply QFT technique, the plant must be represented in frequency domain where the representation can be obtained from state space or Linear Time Invariant (LTI) format (Borghesani et al., 1999). Linear process model provides low order transfer to describe the linear system dynamics of the plant. The input and output data is divided into two parts; As model estimation and model validation. The estimation of the model parameters is done using Prediction Error Minimization (PEM) method (Ljung, 2008). The best performance model obtained based on the highest best fit (Ljung, 2008) is given in equation (1):

$$P(s) = K\frac{1+T_z s}{(1+2\zeta T_W s+(T_W s)^2)(1+T_{p_3} s)}e^{-T_d s} \qquad (1)$$

Where K = 0.17788; Tw = 0.32426; ζ = 0.17533; Tp_3 = 32.076; T_d = 27.027; T_z = 0.47177.

Equation (1) with its parameters value is considered as the nominal plant in QFT design. There are uncertainties in grain drying process as a result of linearization, parameters variation and delay in the process. Therefore, $\pm$5% uncertainty range has been defined for parameters in equation (1). Multiplicative non parametric uncertainty is considered as it will cover larger uncertainty range,

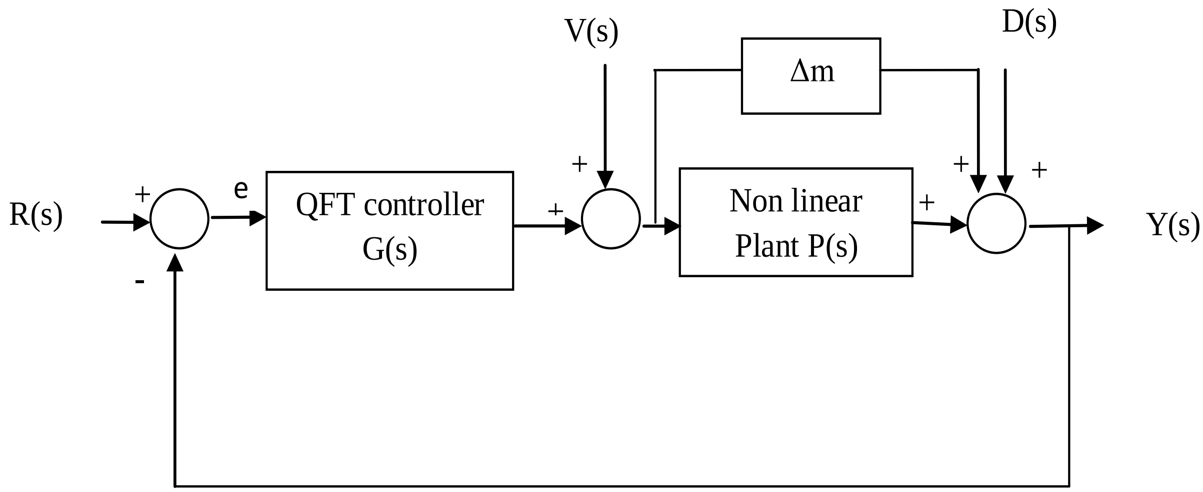

Figure 3. Structure of control system using QFT technique.

Table 1. Random LTI plants parameters.

Plant	K	T_w	ζ	Tp_3	T_z
Sys1	0.14230	0.25941	0.14026	25.66080	0.37742
Sys2	0.17788	0.32426	0.17533	32.07600	0.47177
Sys3	0.21346	0.38911	0.21034	38.49120	0.56612
Sys4	0.14230	0.32426	0.21034	25.66080	0.47177
Sys5	0.17788	0.38911	0.14026	32.07600	0.56612
Sys6	0.21346	0.25941	0.17533	38.4912	0.37742
Sys7	0.21346	0.38911	0.21034	25.66080	0.56612
Sys8	0.14230	0.38911	0.17533	38.49120	0.56612

unmodeled dynamics at high frequencies (Doyle et al., 1990) and delay and parameter loss due to linearization. The block diagram of the grain drying control system is shown in Figure 3. Eight sets of parameters uncertainty were chosen randomly as the LTI plants those cover the minimum and maximum variation of the plant. The LTI plants parameters are summarised in Table 1.

Standard QFT design

The QFT design procedure involves three basic steps (Borghesani et. al., 1999). These steps are; 1) Computation of QFT bounds; 2) Design of controller and possibly pre-filter; 3) Analysis of the design. QFT bounds are generated from the combination of desired specifications and plant templates (results of plant uncertainty) which are converted into magnitude and phase constraints on a nominal open loop function. A nominal open loop function is then designed (via loop shaping) to simultaneously satisfy its constraints as well as to achieve nominal loop stability. Analysis of the design is important to ensure the design requirements are met at defined frequency range. The grain dryer system can be presented by a family of third order transfer functions as the followings:

$$P(s) = k\frac{1 + T_z s}{1 + 2\varsigma T_w s + (T_w s)^2)(1 + T_{p_3} s)}\left(1 + \Delta m(s)\right) \quad (2)$$

Where

$$\Delta m(s) = \frac{0.09252s + 0.186774}{3.904225s^3 + 4.338012s^2 + 33.80516s + 1}e^{-27.027s}$$

;

k = 0.16899 to 0.18677; T_w = 0.30805 to 0.34047; ζ = 0.16656 to 0.18410; T_{p3} = 30.4722 to 33.6798; T_z = 0.44818 to 0.49536.

The uncertainty range considered is ±5% parameters variation; $\Delta m(s)$ is obtained from the transfer function of the grain dryer that gives the highest variation of frequency response of parameter variation (LTI); $\Delta m(s)$ becomes the disk radius in multiplicative non parametric uncertain plant which covers larger uncertainty range. In QFT approach, the controller is designed based on desired specifications which are given as the following:

Robust stability margin;

$$\left|\frac{L(j\omega)}{1 + L(j\omega)}\right| \le 1.2 \quad (3)$$

Robust output disturbance rejection;

$$\left|\frac{Y(j\omega)}{D(j\omega)}\right| < 0.07\left|\frac{j\omega^3 + 64(j\omega)^2 + 748(j\omega) + 2400}{(j\omega)^2 + 14.4(j\omega) + 169}\right|, \quad \omega < 10 \quad (4)$$

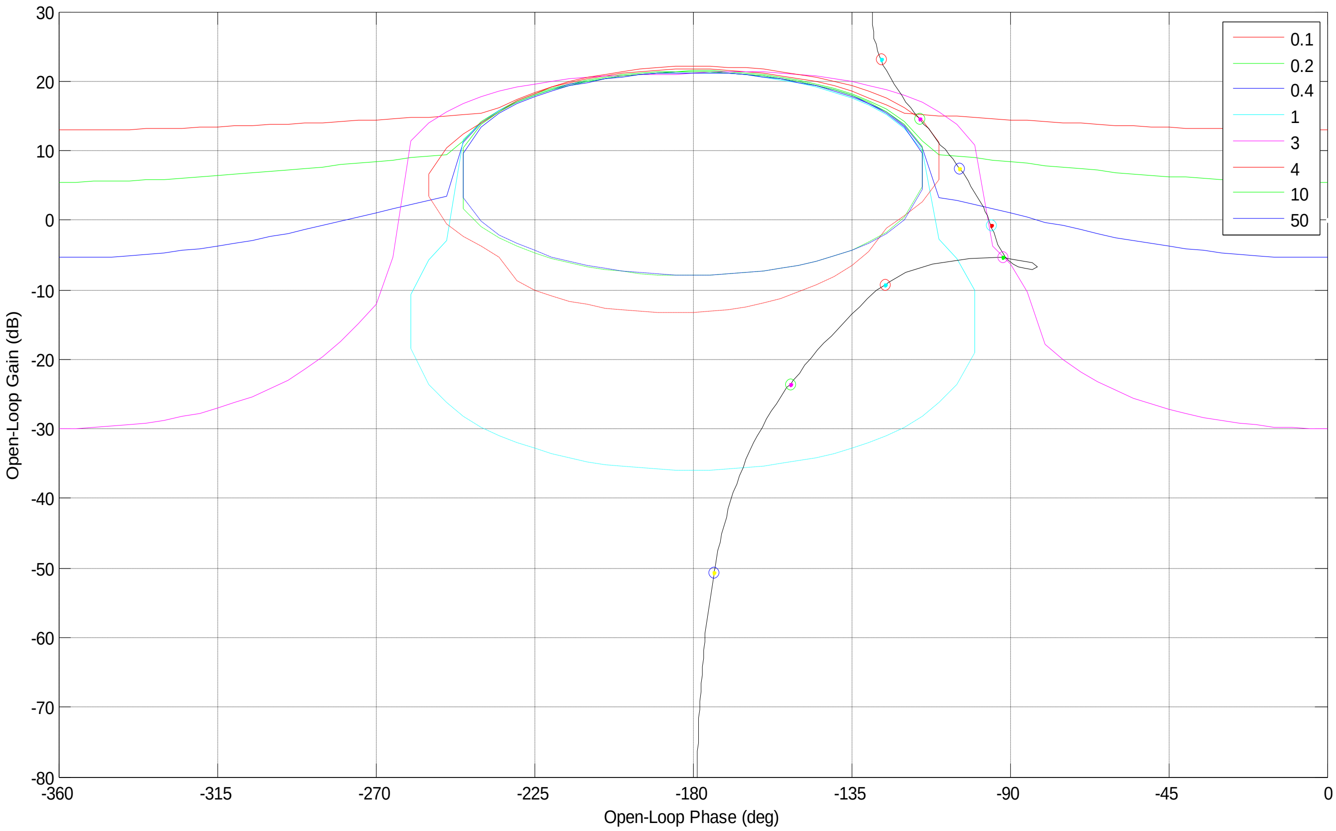

Figure 4. Loop shaping and superposition of all bounds.

Robust input disturbance rejection;

$$\left|\frac{Y(j\omega)}{V(j\omega)}\right| < 0.01, \qquad \omega < 50 \tag{5}$$

Where L (jω) = G (jω)P(jω); L (jω) is the nominal loop, G (jω) is the controller and P(jω) is the plant. As a result from the inequalities in (3), (4) and (5), stability, robust output disturbance rejection and robust input disturbance rejection boundaries are generated.

A QFT-based controller is determined using loop shaping Interactive Design Environment (IDE) (Borghesani et al., 1999) to satisfy these constraints. This IDE helps the designer to design a controller in graphical approach and see the trade-off between controller complexity and performance specifications instantaneously. The superposition of all stability, robust output disturbance rejection, robust input disturbance rejection bounds and the nominal loop obtained from manual loop shaping is shown in Figure 4. Considering low-order controller that can meet the robust performance specifications, the best obtained QFT-based controller for the grain drying process is given by equation (6):

$$G(s) = \frac{296.9056(s+0.1379)(s^2+1.55s+7.95)}{s(s+3)(s+4.93)} \tag{6}$$

The analysis of the design is important to ensure the obtained QFT-based controller meets the desired specifications at all frequencies. Figure 5 shows the analysis of robust margin, robust output disturbance and robust input disturbance. The signals lie below the dotted lines which indicate those signals do not exceed the pre-defined specifications. Therefore the QFT-based controller design for the grain dryer plant is considered successful.

Online QFT-based self-tuning controller

Adaptive element is needed for a grain dryer plant due to some reasons. The parameters variation occurred during drying process might be larger than expected. In standard QFT design methodology, the controller is designed only for a certain uncertainty range. The controller might produce unacceptable response if the parameters variation exceeds the uncertainty range. Therefore, adaptive control is important as it can cope with larger parameters variation and consequently automate the controller's design (loop shaping) which is human dependence. Adaptive control also produces low control effort which is desirable. The online QFT-based self-tuning controller block diagram is shown in Figure 6. The design steps for the proposed online QFT-based self-tuning controller can be summarised as the following:

1. The parameter of the QFT controller designed under standard QFT procedure is used as the initial parameters for the proposed online QFT-based self-tuning controller.
2. During the system operation process, the minimization of the system error function is the main task of the controller. Recursive least square will be used to identify the plant's parameters according to plant changes.
3. Algebraic method (pole placement) with integrated QFT specifications is used to find the optimal values of the controller.
4. By using step 2 at each running step of the system operation, a

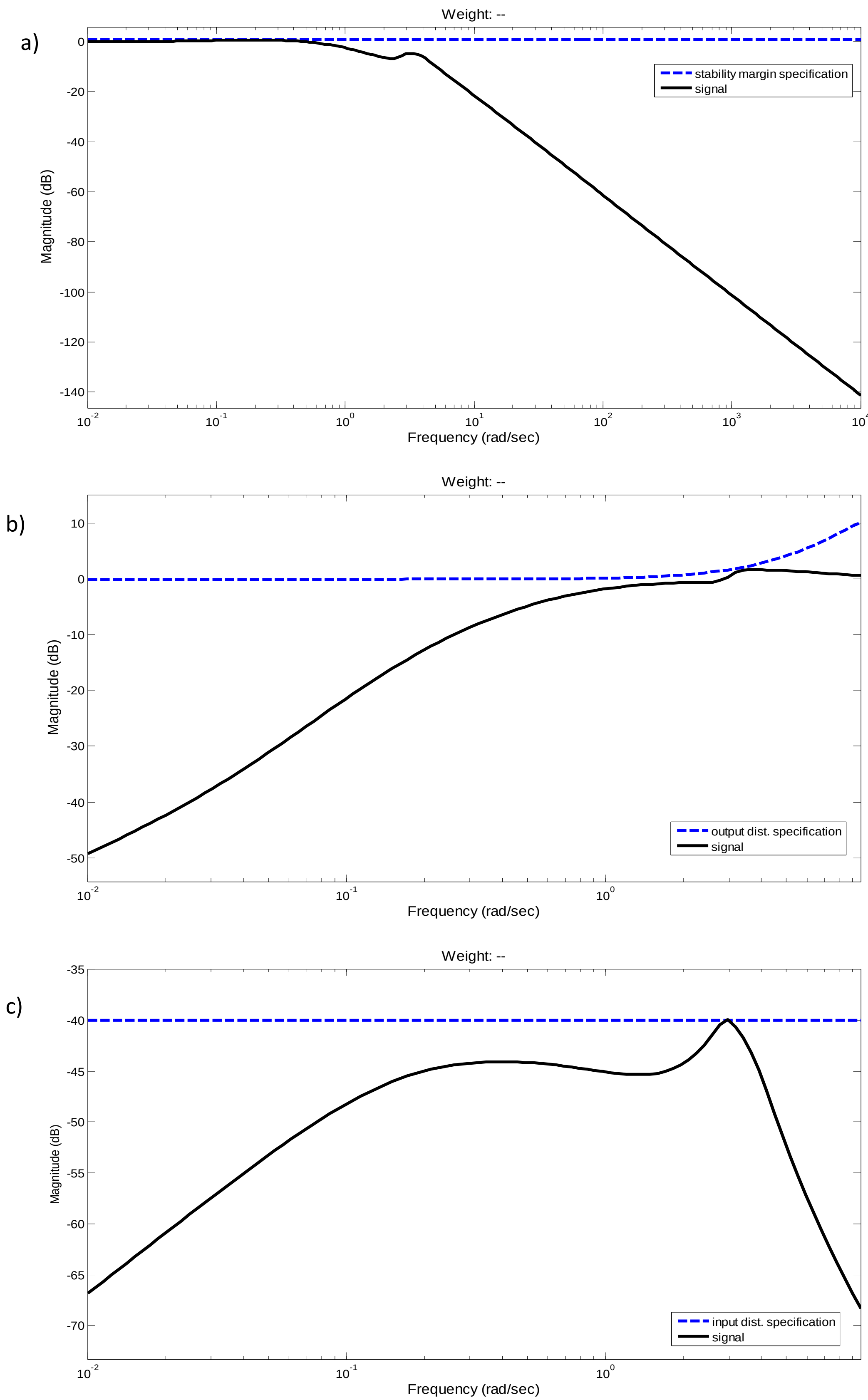

Figure 5. Analisis of the design. a) robust stability margin b) robust output disturbance c) robust input disturbance.

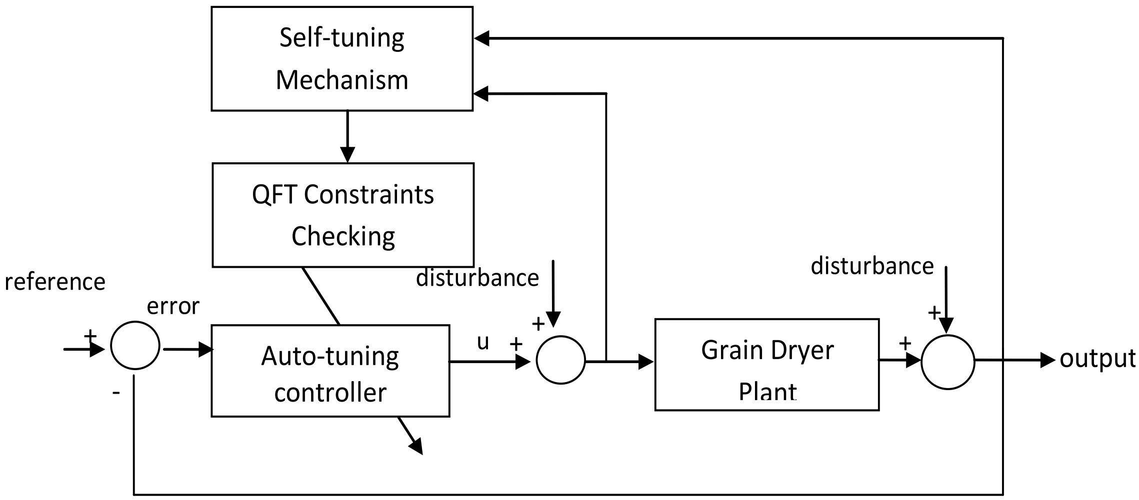

Figure 6. Block diagram of online QFT-based self tuning controller for a grain dryer plant.

new set of the controller's parameters is given, only if condition in step 3 satisfied. The controller will be updated for the next step of time.

The Grain Dryer Plant

In order to apply adaptive control, the continuous transfer function of the plant is converted to discrete using a zero order hold (zoh) and sampling period of 1. Besides its simplicity, ZOH is a typical approach used to make data suitable for feedback control (Triplett and Kristi, 2006). The discrete transfer function of the grain dryer plant is given by equation (7):

$$P(z) = \frac{0.008441z^2 + 0.05282z - 8.75e^{-5}}{z^3 + 0.1889z^2 - 0.7835z - 0.3287} \tag{7}$$

Representing in terms of the output y(k) and previous input u(k), in the form of time shift operator, equation (7) becomes:

$$y(k) = 0.008441\,u(k-1) + 0.05282\,u(k-2) - 8.75e^{-5}u(k-3) - 0.1889\,y(k-1) + 0.7835\,y(k-2) + 0.3287\,y(k-3) \tag{8}$$

In adaptive, the plant is represented in terms of regression as shown in equation (9);

$$\widehat{y_k} = -\widehat{a_1}y_{k-1} - \ldots - \widehat{a_n}y_{k-n} + \widehat{b_1}u_{k-d-1} + \cdots \widehat{b_m}u_{k-d-m} \tag{9}$$

Where $\widehat{a_1}, \ldots, \widehat{a_n}, \widehat{b_1}, \ldots, \widehat{b_m}$ are the current estimations of process parameters. However, the coefficients in equation (8) are very important to be used as the priori information in order to prevent inadequate controller design (Sen, 2006; Bobal et al., 2005).

System identification

Recursive Least Square (RLS), particularly RLS with adaptive directional forgetting has been used to identify to plant model at each running step. In general, equation (9) can be written in vector form (Bobal and Chalupa, 2008):

$$\widehat{y_k} = \theta_{k-1}^T . \emptyset_k \tag{10}$$

Where $\theta_{k-1} = [\widehat{a_1}, \ldots, \widehat{a_n}, \widehat{b_1}, \ldots, \widehat{b_m}]^T$;

$$\Phi_k = [-y_{k-1}, \ldots, -y_{k-n}, u_{k-d-1}, \ldots, u_{k-d-m}]^T$$

Least square objective function is based on minimisation of the sum of prediction errors squares, given by equation (11):

$$J_k = \sum_{i=1}^{k} (y_i - \theta_k^T \phi_i)^2 \tag{11}$$

Where y_i is process output in i-th step whereas $\theta_k^T \phi_i$ is predicted process output. Recursive least square method is obtained when the vector of parameters estimation is updated in each step, according to equation (12):

$$\theta_k = \theta_{k-1} + \frac{C_{k-1}.\phi_k}{1 + \phi_k^T . C_{k-1}.\phi_k} . (y_k - \theta_{k-1}^T \phi_k) \tag{12}$$

Where C is the covariance matrix. The value of C will be updated in each step as given by equation (13):

$$C_k = C_{k-1} - \frac{C_{k-1}.\phi_k.\phi_k^T.C_{k-1}}{1 + \phi_k^T.C_{k-1}.\phi_k} \tag{13}$$

Initial value of matrix C determines influence of initial parameter estimations (priori information) to the identification process. RLS with adaptive directional forgetting will overcome the disadvantage of pure recursive least square method in an absence of signal weighting. In this method, the forgetting coefficient is changed with respect to changes of input and output (Bobal and Chalupa, 2008). From equation (12), the following equations are derived:

$$\theta_k = \theta_{k-1} + \frac{C_{k-1}.\phi_k}{1+\xi}.\left(y_k - \theta_{k-1}^T\phi_k\right) \quad (14)$$

Where $\xi = \phi_k^T.C_{k-1}.\phi_k$ (15)

Matrix C is updated in each step according to equation (16):

$$C_k = C_{k-1} - \frac{C_{k-1}.\phi_k.\phi_k^T.C_{k-1}}{\varepsilon^{-1}+\xi} \quad (16)$$

Where $\varepsilon = \varphi_{k-1} - \frac{1-\varphi_{k-1}}{\xi}$ (17)

Forgetting coefficient is updated as follows:

$$\varphi_k = \frac{1}{a + (1+\rho)\left\{\ln(1+\xi) + \left[\frac{(\upsilon_k+1)\eta}{1+\xi+\eta} - 1\right]\frac{\xi}{1+\xi}\right\}} \quad (18)$$

Where $\upsilon_k = \varphi_{k-1}(\upsilon_{k-1}+1)$ (19)

$$\eta = \frac{(y_k - \theta_{k-1}^T\phi_k)^2}{\lambda_k} \quad (20)$$

$$\lambda_k = \varphi_{k-1}\left[\lambda_{k-1} + \frac{(y_k - \theta_{k-1}^T\phi_k)^2}{1+\xi}\right] \quad (21)$$

Online QFT-based Self-tuning Controller

The controller is an online QFT-based controller. Based on the structure of the previously obtained QFT-based controller, the online self-tuning controller is designed. Pole placement algebraic method with integrated QFT constraints is used to determine the optimal values of the controller's parameters that give the desired response and meet the QFT constraints/specifications. The controller in equation (6) is converted into discrete using zoh and after simplifying:

$$G_K(z^{-1}) = \frac{q_0 + q_1 z^{-1} + q_2 z^{-2} + q_3 z^{-3}}{1 + (p_1 - 1)z^{-1} + (p_1 + p_2)z^{-2} + (-p_2)z^{-3}} \quad (21)$$

Pole placement algorithm works based on achieving desired pre-set poles of the characteristic polynomials (Bobal et al., 2005). Pole placement is chosen because this algorithm has been established to achieve globally stabilised system for Type-1 system with arbitrary zero which is the same case for grain dryer plant model (Zhang, 1993; Zhang and Evans, 1987). The dynamic behaviour of the closed-loop third order process is similar to the second order continuous system. It was found that the best configuration of ζ and ω for the grain dryer system is 4.55 and 1.25 respectively. This configuration gives the desired percentage of overshoot = 20% and settling time = 6 sampling events. The characteristic equation of the closed-loop grain drying system is given by equation (22).

$$\begin{aligned}(1 + a_1z^{-1} + a_2z^{-2} + a_3z^{-3})(1 - z^{-1})(1 + p_1z^{-1} + p_2z^{-2})&\\ + (b_1z^{-1} + b_2z^{-2} + b_3z^{-3})(q_0 + q_1z^{-1} + q_2z^{-2} + q_3z^{-3})&\\ = -1.1322z^{-1} + 0.3206z^{-2}&\end{aligned} \quad (22)$$

Equation (22) is solved by comparing coefficient of the same power. Matlab Polynomial Toolbox has been used to solve this equation.

After the controllers parameters are obtained, a decision need to be made. Only set of controller's parameters that satisfy the QFT constraints will be accepted. This added robustness criterion makes the controller robust and adaptive. The controller is now called online QFT-based self-tuning controller. Alternatively, the design procedures of the proposed controller are shown in the flowchart of Figure 7.

RESULTS

In the first test, repetitive step signals between 0.17 to 0.14 were inserted to the input of the grain dryer. The plant is operated under nominal condition. As shown in Figure 8, the proposed online QFT-based self-tuning controller successfully tracks the moisture content reference signal. The transient response has large percentage overshoot and settling time at the beginning of the response but the response gradually improved. The overshoot diminished and settling time reduced significantly after the third pulse. The response is stable with no steady state error and low control signal (between 0.3V to 2V). Figure 9 shows six estimated model parameters changing as the reference signal are changed.

When a step input disturbance of magnitude 0.1 was applied, the proposed online QFT-based self-tuning controller successfully attenuates the effect of input disturbance. As shown in Figure 10, the efficiency of the adaptive control is proven as the control signal produced is very low, ranging from 0.3 to 1.6.

Step output disturbance of magnitude 0.01 (approximately 7%) was applied at sampling event = 300. From the results shown in Figure 11, the response produced by QFT-based self-tuning controller is very robust towards step output disturbance.

Uncertainty test was performed to reveal the improvement of the transient performance produced by online QFT-based controller compared to the standard QFT-based controller. In this uncertainty test, the grain dryer plant model was tested with three stages of uncertainty ranges, i.e. 5%, 20% and 50% parameters variation. The parameters variation occurred at sampling event = 300. From the test result shown in Figure 12, online QFT-based controller produced slower settling time and higher percentage overshoot due to adaptation process. As proven in adaptation test (Figure 8), the transient response improved gradually as number of sampling event increases. However, both standard and online QFT-based controllers reacted quickly towards the plant change. Both of them produced small control signal. Nevertheless, when larger plant change or uncertainty occurred (20% parameters variation), the online QFT-based self-tuning controller adapted better towards the plant change. Referring to Figure 13, it can be seen that the online QFT-based self-tuning controller has smaller percentage of overshoot and shorter settling time compared to the standard QFT-based controller. The performance of online QFT-based self-tuning controller is

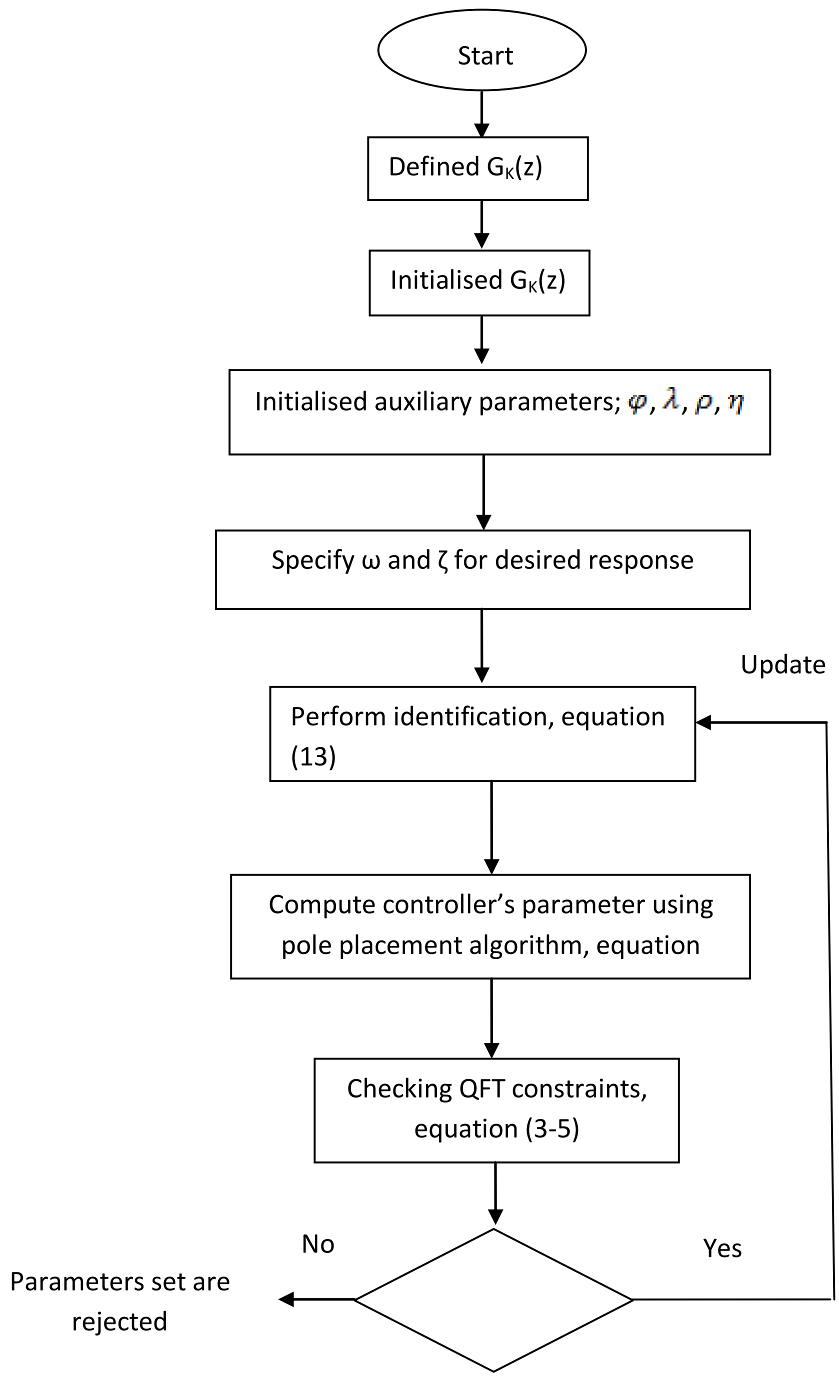

Figure 7. Flow chart of design procedure of the proposed online QFT-based self-tuning controller.

further improved when 50% parameters variation is considered. When the plant experiences very large parameters variation, the online QFT-based self-tuning controller slowly reduced the grain moisture content to the desired level. This effect is shown in Figure 14. Unlike online QFT based self-tuning controller, the offline controller produced undesirable response. The transient response characteristics based on the uncertainty test are summarised in Table 2.

DISCUSSION

The ability of the proposed online QFT-based controller

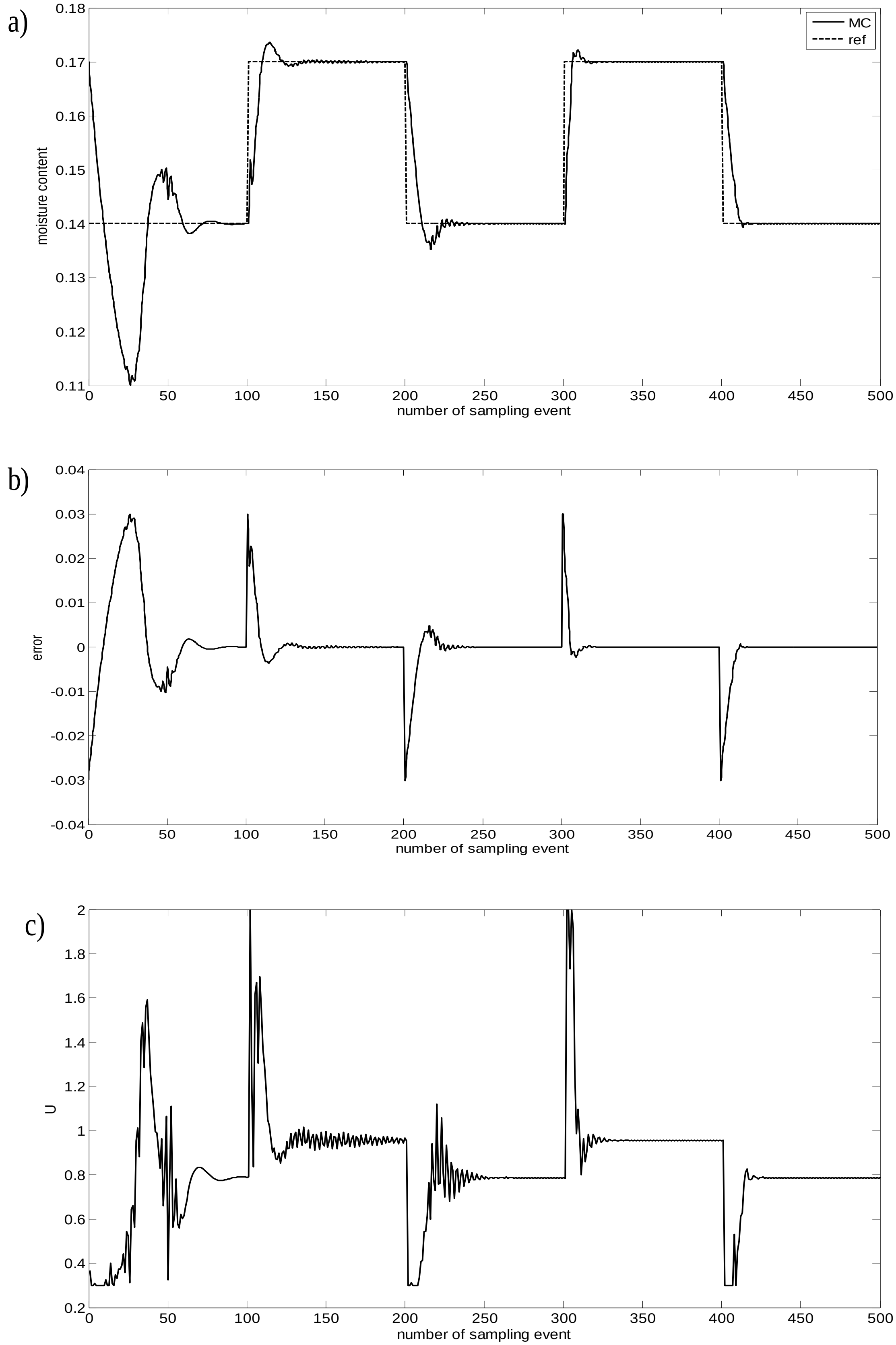

Figure 8. a) The response of the grain dryer control system for nominal plant with QFT-based Self-tuning controller. b) Error signal c) control signal.

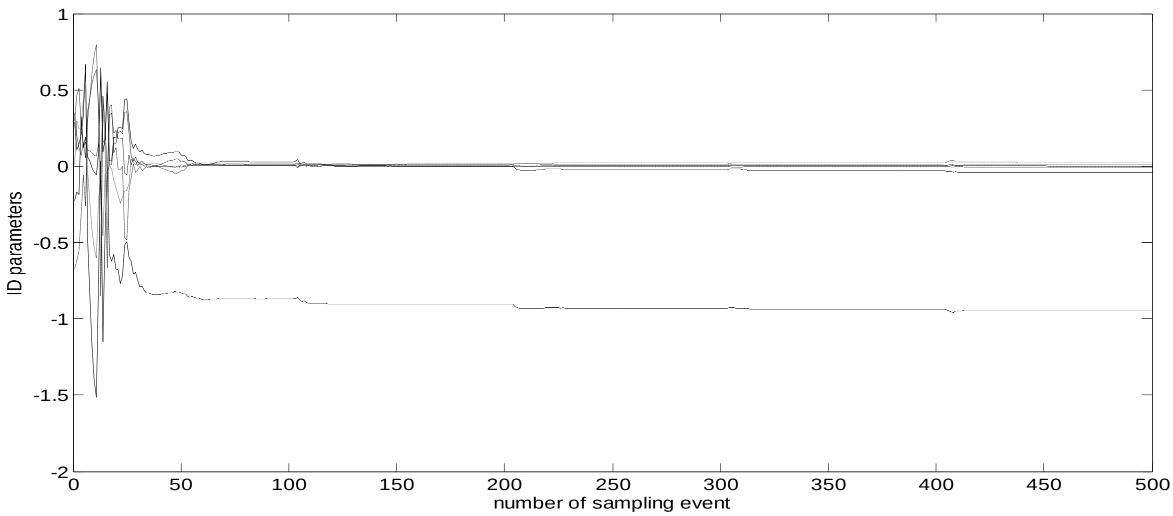

Figure 9. Estimated grain dryer model parameters; a1, a2, a3, b1, b2 and b3.

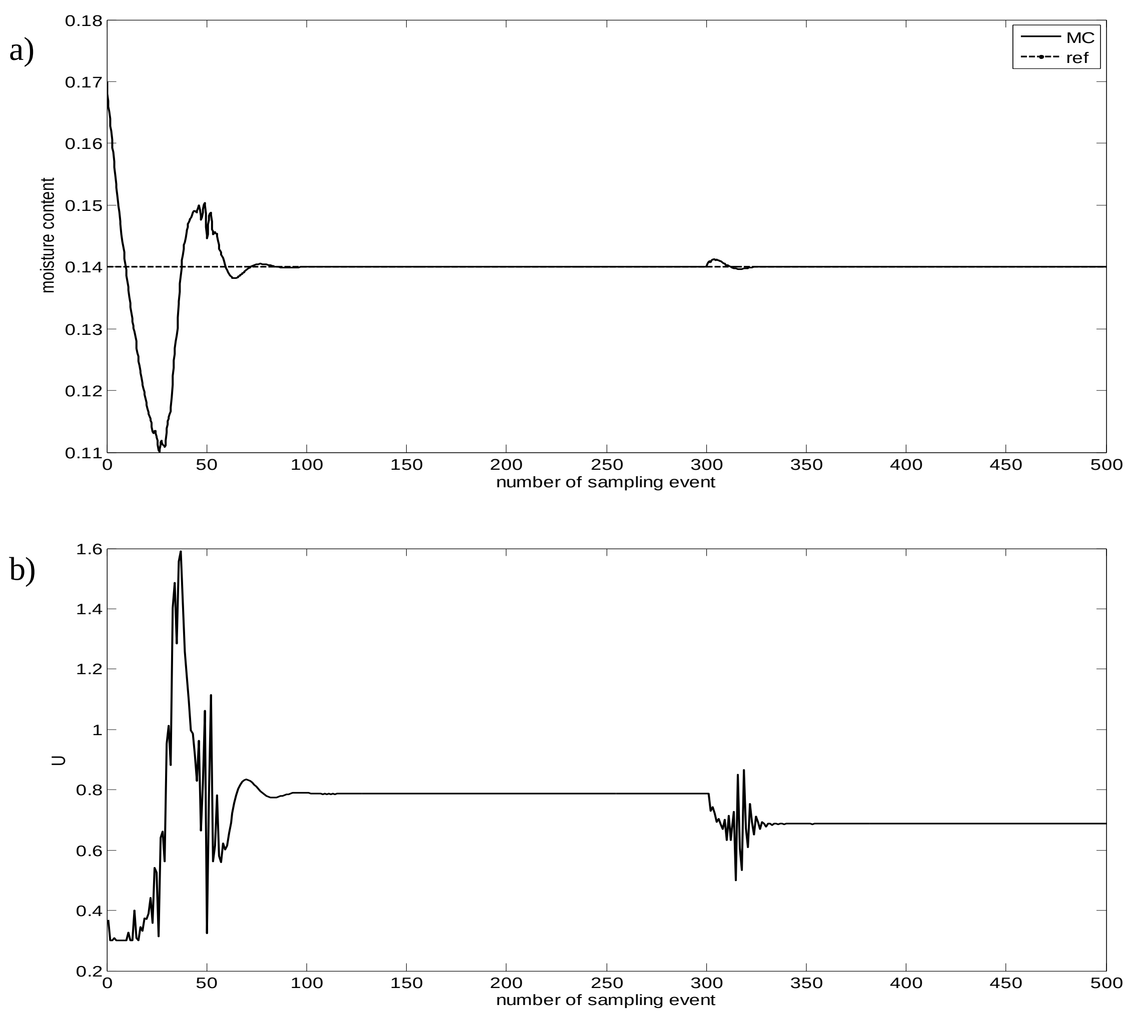

Figure 10. Response of the grain dryer control system with QFT-based self tuning controller towards step input disturbance. a) grain moisture content at output b) control signal.

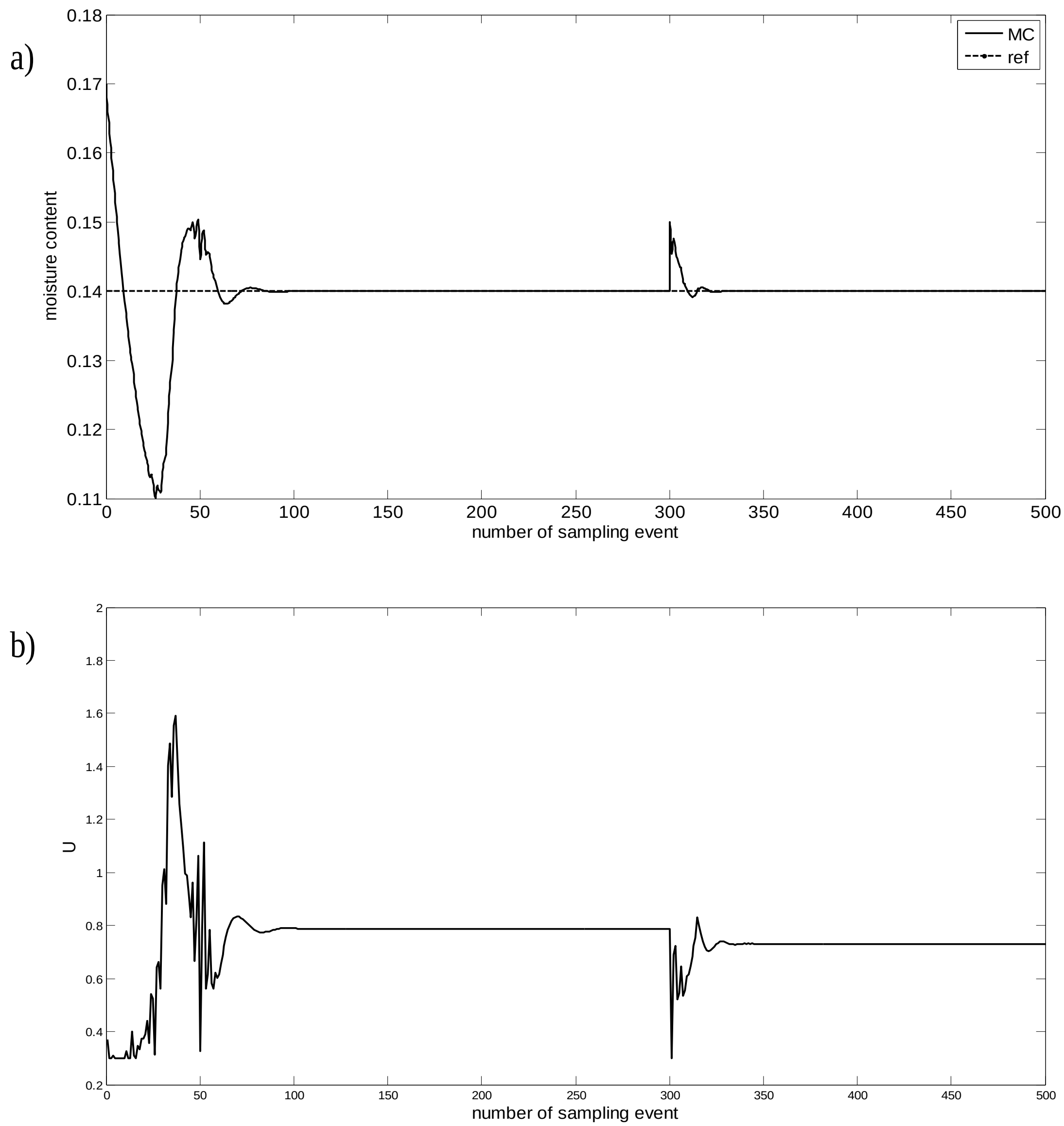

Figure 11. Response of the grain dryer control system with QFT-based self tuning controller towards output disturbance. a) grain moisture content at output b) control signal.

to adapt from initial to desired grain moisture content has been proven. The transient response has been improved where the percentage of overshoot and settling time are gradually reduced throughout the adaptation process. From the test results, the proposed controller is found very robust towards input and output disturbances, as well as parameters variation. Nevertheless, the plant is more affected to output disturbance because output disturbance has direct effect to the grain dryer final moisture content. The control signal produced is also very small.

Compared to standard or offline QFT-based controller, online QFT-based controller has the advantage when dealing with larger parameters variation. This is proven when 20% and 50% parameters variation occurred on the plant. Undesirable results obtained by the standard QFT-based controller because the parameters variation exceeds the defined uncertainty range. On the other hand, online QFT-based controller still produces good result. Robust stability, input and output disturbance are guaranteed as the QFT constraints are checked at every sampling event.

Conclusions

In this paper, an online QFT-based self-tuning controller for a grain dryer plant was successfully designed and

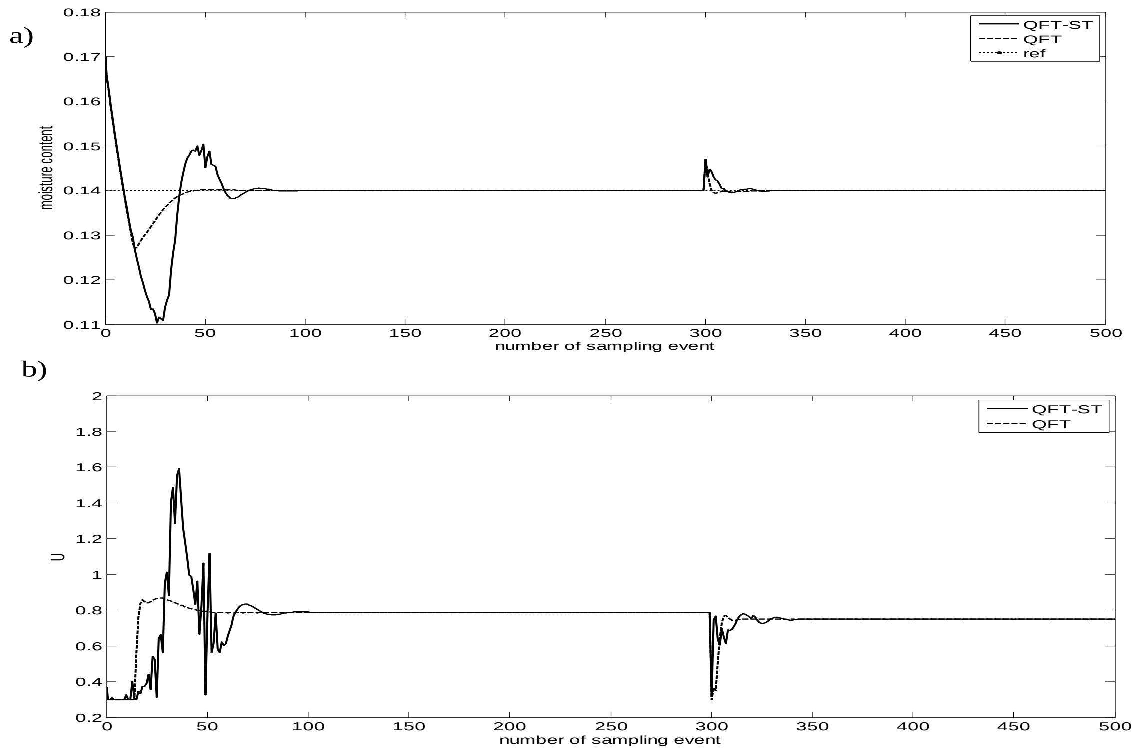

Figure 12. Performance comparisons between offline and online self-tuning QFT-based controllers towards 5% parameters variation a) grain moisture content at output b) control signal.

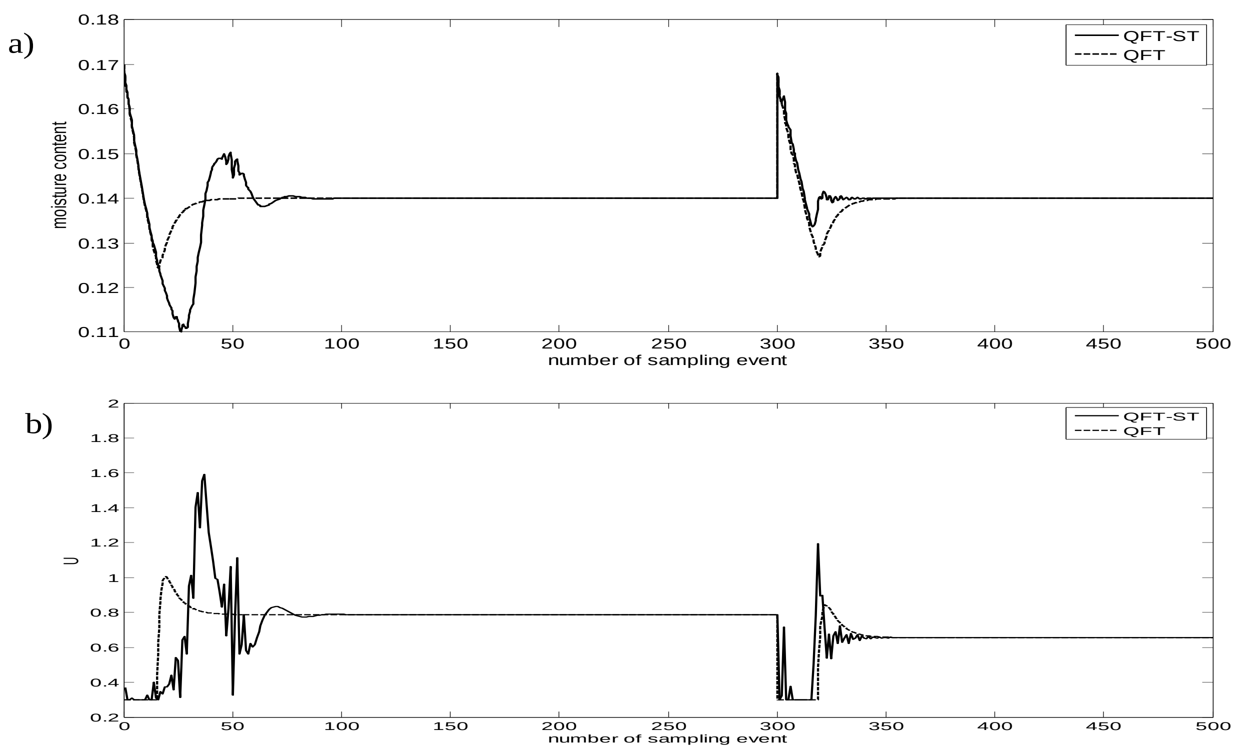

Figure 13. Performance comparisons between offline and online self-tuning QFT-based controllers towards 20% parameters variation a) grain moisture content at output b) control signal.

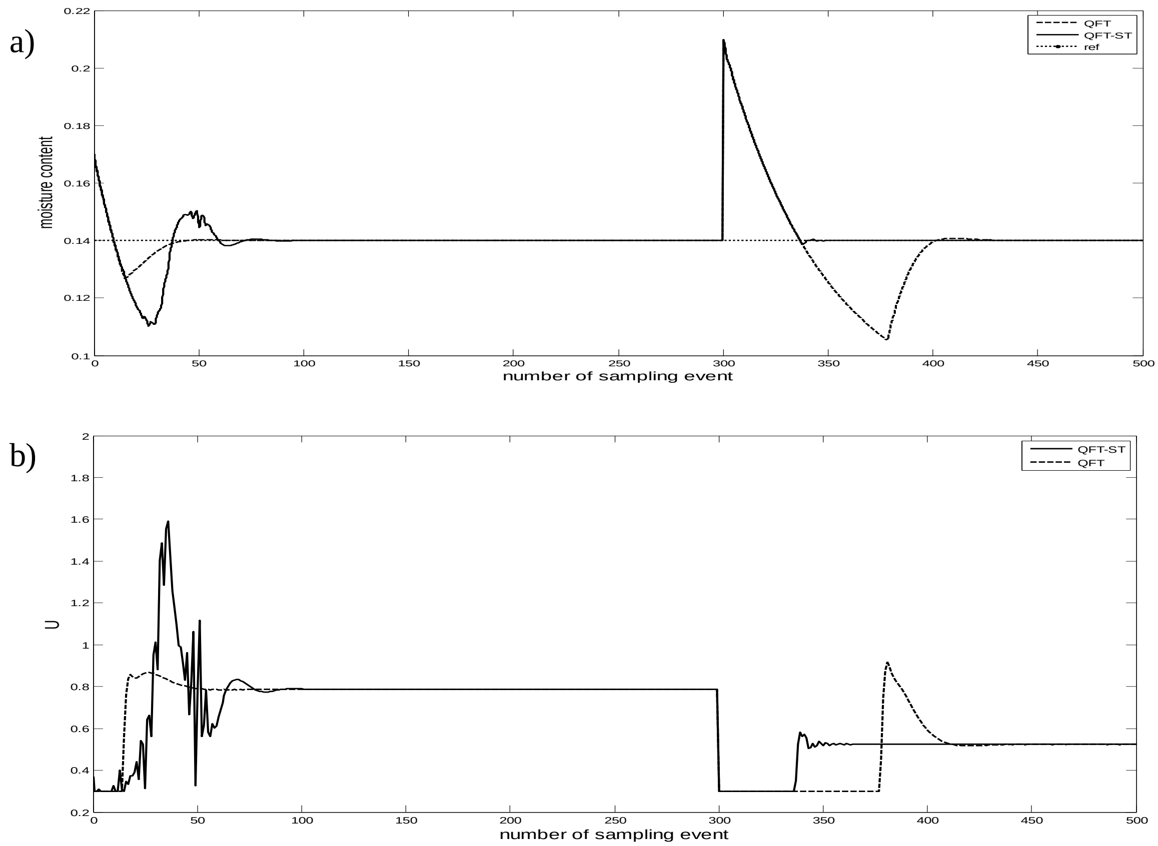

Figure 14. Performance comparisons between offline and online self-tuning QFT-based controllers towards maximum 50% parameters variation a) grain moisture content at output b) control signal.

Table 2. Summary of transient responses of offline and online QFT.

	Offline QFT			Online QFT-Self-tuning		
	5% variation	20% variation	50% variation	5% variation	20% variation	50% variation
Settling time	2	29.7	96	4	18.5	36.5
Percentage overshoot	-	9.286%	25%	-	4.571%	0.929%
Steady state error	0	0	0	0	0	0

validated. It has several advantages over standard QFT design especially when the parameters' variations are large and exceed the defined uncertainty range. An online QFT-based controller produced smaller percentage overshoot and shorter settling time than standard QFT-based controller when the grain dryer plant experienced larger parameters' variations. The controller's design is done online; instantaneously it avoids dependency of human skill in loop shaping. Therefore, when plant uncertainty range is suddenly changed, no redesign of controller is required as in standard QFT-based controller. Adding QFT constraints into the self-tuning algorithm ensures the robustness of self-tuning controller (robust stability, input and output disturbances).

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