MODEL-BASED AND MODEL-FREE CONTROL ALGORITHMS FOR TEXTILE PROCESSES

by

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ABSTRACT

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Textile processes consist of several control loops that require accurate reference tracking. One of the most crucial control loops is the temperature control where the temperature of the corresponding medium must track the reference value with sufficient accuracy to obtain a high-quality textile product. Even though several studies can be found on designing control algorithms for industrial processes in the literature, none of them focus particularly on the aforementioned textile processes. In this study, in order to achieve successful control, several adaptive control algorithms are developed. In addition, corresponding processes are modelled, and a simulation environment is built to increase the speed and safety of development works.

Modelling is realized by dividing the corresponding process into several regions of operation, preparing sub-models for each region and building a composite model by combining these sub-models. A simulation environment is created by examining currently used control algorithms and process dynamics. The simulations of designed models result in significant accuracies. A model-based control algorithm, based on the Model Predictive Control (MPC) approach that utilises previously designed process models, is developed and verified in the simulation environment. Two model-free control algorithms, referred to as Adaptive PI Control and Error Predictive Control (EPC), are developed and verified not only in the simulation environment but also in the field.

ÖZET

TEKSTİL PROSESLERİ İÇİN MODEL TABANLI VE MODEL TABANLI OLMAYAN KONTROL ALGORİTMALARI

Tekstil prosesleri doğru referans takibi gerektiren birçok kontrol döngüsü içermektedir. Bu kontrol döngülerinin en önemlilerinden biri olan sıcaklık kontrolde, yüksek kalitede tekstil ürünü elde etmek için ilgili ortamın sıcaklığı referans değerini yeterli doğrulukta takip etmelidir. Literatürde endüstriyel prosesler için kontrol algoritmaları tasarlamaya yönelik birçok çalışma bulunsa da hiçbiri bahsi geçen tekstil proseslerine özellikle odaklanmamaktadır. Bu çalışmada, başarılı kontrole ulaşmak için birçok uyarlamalı kontrol algoritması geliştirilmiştir. Ek olarak, geliştirme işlerini hızlandırmak ve güvenli hâle getirmek için ilgili prosesler modellenmiş ve bir simülasyon ortamı inşa edilmiştir.

Modelleme, ilgili prosesleri birkaç bölgeye ayırma, her bir bölge için alt modeller inşa etme ve bu alt modelleri birleştirerek bir bileşik model inşa etme şeklinde gerçekleştirilmiştir. Güncel olarak kullanılmakta olan kontrol algoritmaları ve proses dinamikleri incelenerek bir simülasyon ortamı yaratılmıştır. Tasarlanan modellerin simülasyonu kayda değer doğrulukla sonuçlanmıştır. Hâlihazırda tasarlanan modelleri kullanan ve Model Öngörülü Kontrol (MÖK) yaklaşımına dayanan bir model tabanlı kontrol algoritması geliştirilmiş ve simülasyon ortamında doğrulanmıştır. Uyarlamalı PI Kontrol ve Hata Öngörülü Kontrol (HÖK) olarak adlandırılan iki model tabanlı olmayan kontrol algoritması geliştirilmiş ve sadece simülasyon ortamında değil sahada da doğrulanmıştır.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS

A	State transition matrix of MPC model
A_c	Constraint matrix of MPC
A_L	Least squares matrix
A_t	Surface area of the material
b_c	Cost matrix of MPC
B	Input matrix of MPC model
c_1	Continuous adaptive PI proportional gain tuning coefficient
c_2	Continuous adaptive PI integral time tuning coefficient
C	Output matrix of MPC model
c_L	Least squares vector
D	Direct transition matrix of MPC model
$\overline{f}$	First optimization matrix
G	Controller amplitude
G_c	RPC controller transfer function
G_h	Relay input amplitude
G_p	RPC process transfer function
G_{rpc}	RPC transfer function of rate prediction
G_{tds}	RPC transfer function of time delay
G_u	Relay output amplitude
$\overline{h}$	Average heat transfer coefficient
$\overline{H}$	Second optimization matrix
$\overline{h}_m$	Mass transfer coefficient
J	MPC cost function
K_1	RPC process gain
K_2	Maximum rate of change of RPC/EPC control variable
K_3	RPC/EPC sensitivity band
K_4	EPC dead band
K_{adap}	Proportional gain default adaptation coefficient

$\overline{K}_{adap}$	Proportional gain current adaptation coefficient
K_p	Proportional gain of PI controller
$\overline{K}_p$	Current proportional gain of PI controller
K_{pn}	Ultimate proportional gain of PI controller
$\dot{m}_{ev}$	Mass transfer per second
p_A	Air pressure
p_t	Surface pressure
Q	Transferred heat
R^2	R-Square value
$SS_{residue}$	Residual sum of squares
SS_{total}	Total sum of squares
T_0	Initial temperature
T_A	Air temperature
T_D	Derivative time of PI controller
T_i	Integral time of PI controller
T_{in}	Ultimate period value
T_{hor}	EPC prediction horizon
$T_{Machine}$	Machine temperature
T_{past}	EPC prediction past
T_{Steam}	Steam temperature
T_t	Surface temperature of the material
u	Control input
U_{high}	High relay parameter
U_{low}	Low relay parameter
U_{max}	Maximum relay parameter
U_{min}	Minimum relay parameter
V	MPC constraint parameter
Y	RPC control variable
Y_{sp}	RPC set point of control variable
z	Optimum control input

ΔT_1	First adaptation band parameter
ΔT_2	Second adaptation band parameter
Δu	Difference between current and previous control input
η_{MV}	Harris Index
σ	Standard deviation
σ^2	Variance
σ^2_{MV}	Variance of MVC applied process
σ^2_y	Variance of real process

LIST OF ACRONYMS/ABBREVIATIONS

AR	Autoregressive
EPC	Error Predictive Control
FOPTD	First Order Plus Dead Time
LPF	Low Pass Filter
MAE	Mean Absolute Error
MIMO	Multiple Input Multiple Output
MSE	Mean Squared Error
MPC	Model Predictive Control
MVC	Minimum Variance Control
OV	Overshoot
P	Proportional
PI	Proportional-Integral
PID	Proportional-Integral-Derivative
PLC	Programmable Logic Controller
PV	Present Value
QP	Quadratic Programming
RMSE	Root Mean Squared Error
RPC	Rate Predictive Control
SP	Set Point
SSE	Steady State Error
St. Dev.	Standard Deviance
Var.	Variance

1. INTRODUCTION

Textile industry has existed since the beginning of the industrial revolution and maintains its importance up to the present. It began in modest workshops which were powered by physical human labour and has progressed to today's factories, which are powered by electricity and mostly controlled autonomously. There are different types of textile processes such as singeing, bleaching, dyeing and drying that are applied either once or several times throughout a complete textile cycle. There are several variables like temperature, pressure, flow and pH that are controlled in a single textile process. Each of these variables has its own thermodynamic and mechanical properties and controlling all of them in the desired manner is not an easy task to execute. In order to achieve the desired control specifications, it is crucial to develop adaptive control algorithms to minimize the effects of disturbances and adapt to both internal and external changes.

Adaptive control algorithms can be designed based on two approaches: model-based approach and model-free approach. In the model-based approach, a process model is utilised to update the control input according to the predictions of the corresponding model. On the other hand, in the model-free approach, control input updates are made without utilising any process model. Instead, internal dynamics and past output data of the process are used. Adaptive control algorithms will be developed for textile processes through the collaboration of these two approaches.

The textile industry is massive, consisting of various physical and chemical processes throughout the production of textile materials. The standard flow of the textile processing steps is shown in Figure 1.1. Initially, a grey fabric, referring to knitted fabrics or unfinished woven, is singed, during which open-width fabric is passed over a gas flame so that protruding fibres can be burned out. Then, sizing agents are removed from the fabric in the desizing operation.

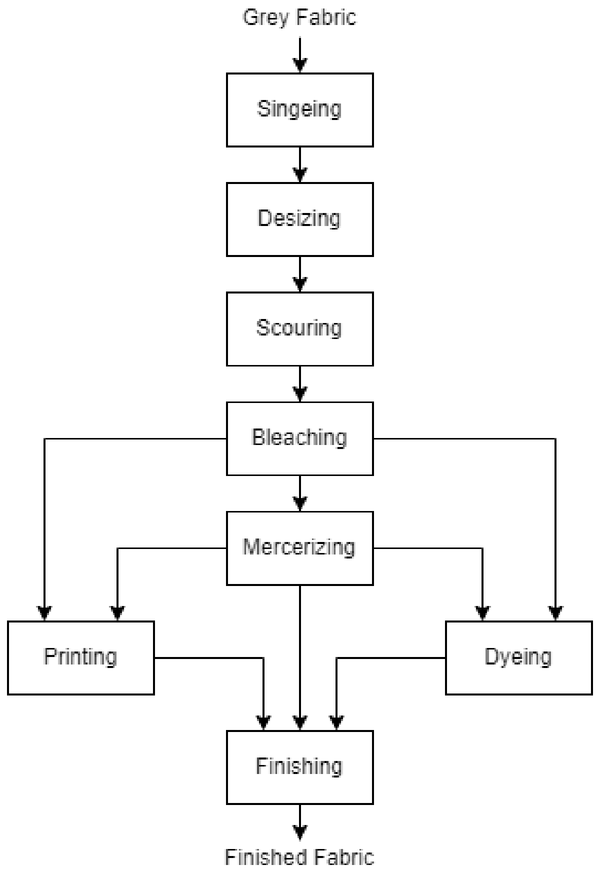


Figure 1.1. General steps in textile processing [1].

In scouring, natural and acquired impurities are removed from the fabric to make it more suitable and absorbent for the following processes. Later on during bleaching, all colouring materials are cleared away from the fabric and a whiter look is ensured. If the fabric is in need of enhancements of its various properties like chemical reactivity or tensile strength, mercerization is performed. Dyeing and printing are two major processes applied for the colouring of textiles. In dyeing, the corresponding textile substrate is brought into contact with the solution of a colourant, after which the substrate takes in the said colourant. Meanwhile in printing, one or more textile dyes or pigments are applied on textile products in the form of a pattern or design. Finishing treatments like drying and softening are applied at the end to improve the appearance and other aesthetics of the textiles [1]. Textile processes that are included in the scope of this thesis are drying, which is a part of the finishing processes, and dyeing processes.

1.1. Drying Processes

In drying processes, textile products with various masses, volumes and humidity rates are dried by industrial drying machines that have various capacities, types and power. Drying processes are divided into 4 categories depending on the heat transfer mechanism, which are convection, conduction, radiation and high-frequency drying [2]. Industrial drying machines, which are available in 3 different drying types as in electrical, steam and gas, have drying capacities ranging from 10 kg up to 340 kg [3], [4]. The type of drying machines which will be dealt with in the scope of this thesis is steam drying machines. A drying machine example can be seen in Figure 1.2.

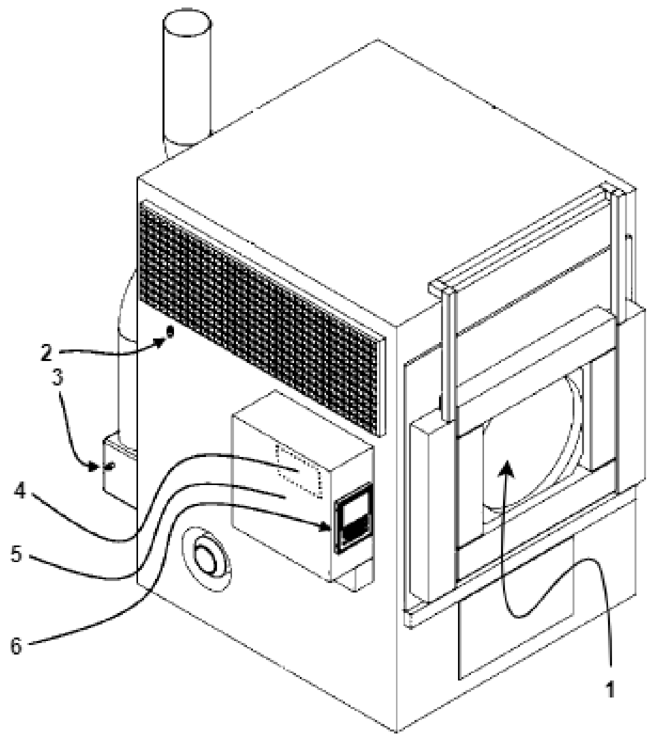


Figure 1.2. A drying machine example | 1. Drum 2. Relative humidity sensor 3. Temperature sensor 4. Processor 5. Controlling Unit 6. User interface.

Textile products placed inside the drum of the drying machine are dried by transferring heat from high temperature air, which is heated by an exchanger mechanism that utilises high temperature steam. While the drying process continues, the drum moves clockwise and counter-clockwise periodically to be able to homogenize the heat transfer. After the temperature and relative humidity are read by corresponding sensors simultaneously, information is fed back to the controlling unit which contains a processor and controls the whole process by opening and closing several valves and pumps. A controlling unit example is shown in Figure 1.3. Necessary process configurations are made by the operator via the user interface. The drying process continues until a predetermined time limit is reached or the corresponding textile products become completely dry.

Figure 1.3. A controlling unit example.

The fundamental system variable that is controlled throughout the drying process is the temperature of the air inside the drum. The main control objective of the drying process is to regulate the air temperature in a convenient and stable manner to reach certain dryness and shrinkage characteristics of the related textile products. It is a closed-loop control mechanism that has the air temperature value, which is measured by appropriate sensors, as the main feedback variable. The system variable that will be modelled in the scope of this thesis for drying processes is the temperature of the air inside the drum.

1.2. Dyeing Processes

Dyeing processes have a more complex mechanism compared to drying processes. In dyeing processes, while fabrics like yarn and wool are being dyed, a lot of system variables such as temperature, flow, pressure, liquid level and pH are controlled to be able to achieve the desired fabric quality. Fabric capacity of industrial dyeing machines ranges from 25 kg up to 2500 kg. The pump power of these industrial dyeing machines varies between 15 kW and 55 kW [5], [6]. An example of a fabric dyeing machine is displayed in Figure 1.4.

The corresponding fabric is dyed mainly in the dye kier with the help of reserve and additional tanks by dosing. Various chemicals are injected into the dye liquid concurrently so as to attain the desired dye liquid and fabric characteristics such as colour or pH. The temperature of the liquid is increased or decreased by an exchanger through which it is circulated. The temperature sensor reads the dye liquid temperature and feeds it back to the controlling unit while the process continues. A level sensor is also used to monitor the dye liquid level. Factors like ease of control, capability of gathering sufficient data and need for improvement in control are considered while determining system variables to model and develop adaptive control algorithms. The temperature of the dye liquid is determined as a system variable to model and develop adaptive control algorithms after analysing a great of number processes from different textile dyehouses.

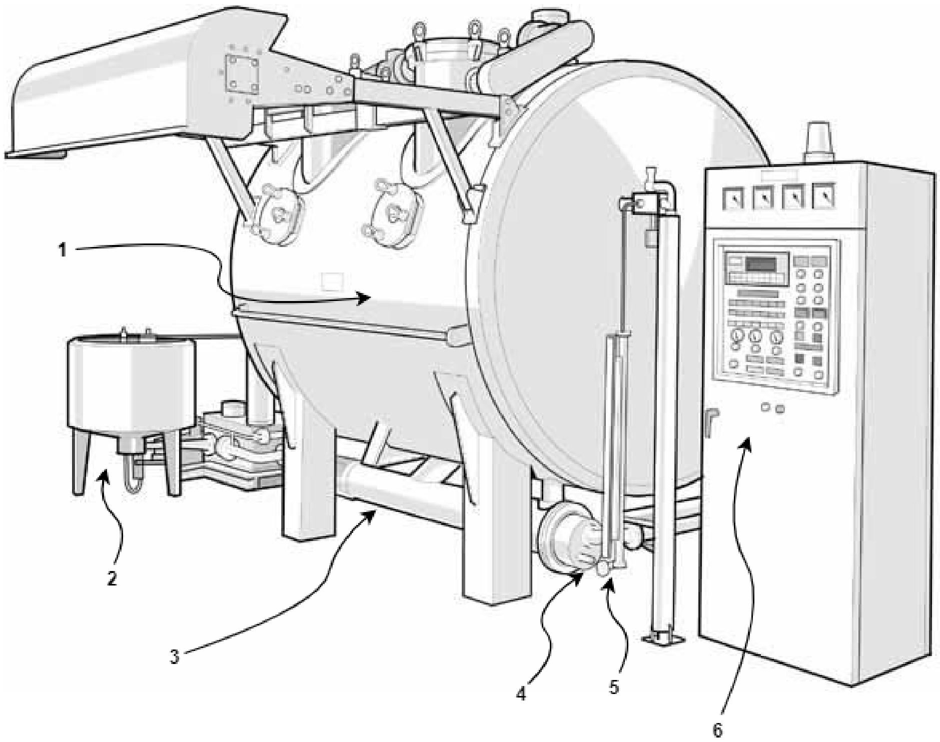


Figure 1.4. A fabric dyeing machine example | 1. Dye kier 2. Reserve tank 3. Exchanger 4. Temperature sensor 5. Level sensor 6. Controlling unit.

The temperature control in dyeing processes differs from the temperature control in drying processes as follows: In dyeing processes, the temperature of the dye liquid, in which the corresponding fabric floats, is controlled. All of these procedures affect temperature control directly or indirectly. A sufficient amount of data are collected from different textile dyehouses that have various process characteristics. Crucial data to develop models and control algorithms are extracted and prepared with the purpose of analysis and efficient utilisation.

1.3. Related Work

There are several studies in the literature dealing with the development of adaptive control algorithms for textile processes. These studies are mainly divided into two parts: modelling and developing control algorithms for these textile processes. In order to model them, we should first understand their theoretical background and process characteristics that are driven by thermodynamic laws. In [7], the fundamentals of textile drying are presented by stating the thermodynamic laws related to variables of drying like heat, mass, air pressure etc. The dynamic structure of textile drying is also presented by observing several batches of drying processes and generalizing the relations between the process variables. An example exhaust air temperature graph of a batch drying process can be seen in Figure 1.5.

In [8], a convective drying model is proposed to describe the drying behaviour of leather. This mathematical model is used to anticipate with reasonable accuracy transient variations in temperature and moisture content distribution of leather in the dryer, the effect of the temperature and humidity of the dryer, the initial moisture content of leather and the prediction of heat and mass transfer coefficients.

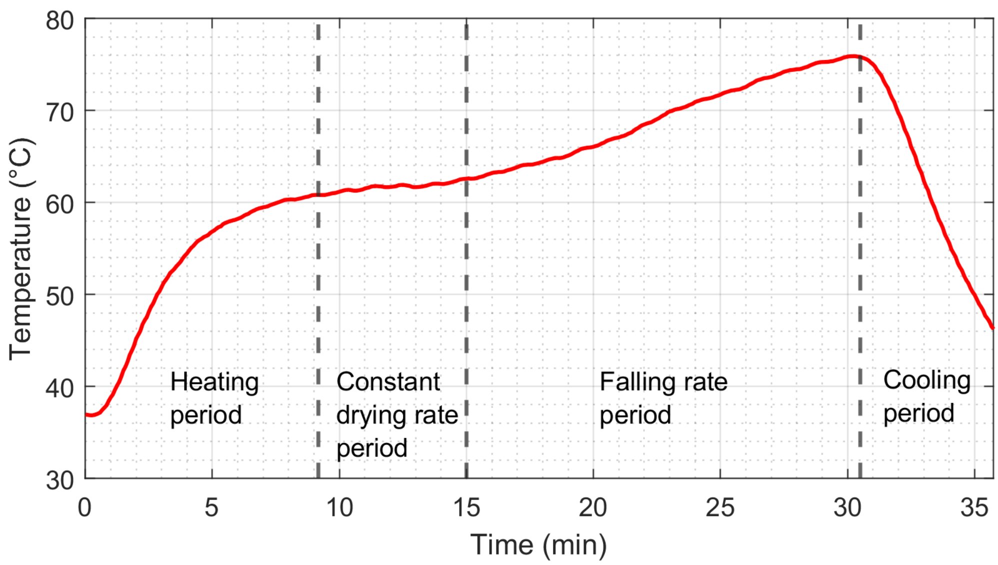


Figure 1.5. Temperature of the exhaust air leaving the drum during a drying process in an open cycle tumble dryer with the dominant drying periods indicated [7].

In [9], a model is developed to represent the convective drying processes of textile materials. The mathematical model was developed from energy and mass balances. The model equations, for which the temperature and humidity of both air and the textile material are unknowns, were written as a system of ordinary equations. Compared with the experimental data obtained from the literature, the simulation results achieved R-squared values above 0.997, indicating that the modelling was predictive in all simulations.

In [10], a simple first order model is constructed and the parameters of the model are determined for the drying dynamics of a wet fabric continuously passing through an infrared oven, using a method involving off-line (batch) data processing. The results show that a simple first-order model represents the dynamics characteristics of the oven just as well as a higher order, thus providing an important advantage for elaborating an efficient numerical controller for the drying process.

In [11], a mathematical modelling and simulation framework is developed on the MATLAB-SIMULINK platform for the rotary dryer. The model is semi-empirical based on the first principles, using mass balance and moisture balance equations amongst the vegetables and hot air. Later, a discretised mathematical model for textile dryer machines has been developed by modifying the rotary dryer model. The simulation results of the rotary dryer model are in agreement with the results that are taken as reference.

In [12], the problem of determining the optimal temperature setpoint in realtime for convective textile drying processes is addressed. By means of an Extremum Seeking Control (ESC) scheme, a model-free approach, the dryer operating temperature that ensures a final (desired) residual moisture content in textile materials is determined. The effectiveness of the proposed approach is confirmed by Matlab-based simulations.

In [13], a fuzzy logic based control algorithm is proposed to control dyeing machine temperature. The model of the temperature control system of the dyeing machine is built based on the principle of fuzzy logic control. After being simulated by the use of MATLAB's fuzzy logic toolbox, a comparative simulation of the proposed temperature control system of the dyeing machine has been accomplished. It is concluded that the temperature system can achieve a higher steady-state precision.

In, [14], the temperature control system of a dyeing machine in the textile industry is analysed, the PLC technology to automatically control the temperature is adopted and the automatic temperature adjustment during the operation of the dyeing machine is attained. It is therefore proved that this method could fulfil the basic requirement of temperature in the dyeing machine.

In [15], SM-MAC control algorithm based temperature control method in an airflow dyeing machine is presented. The SM-MAC control algorithm is based on two models: one of them is the prediction model, which is the internal model; the other is the reference model. In airflow dyeing machines, the SM-MAC method adapts to the temperature system's characteristics -complex model and large delay. It is concluded that the method not only guarantees good tracking and exact control accuracy of the control system, but also improves the response speed of the control system and the control quality.

In [16], a Generalized Predictive Control (GPC) is introduced, which is applied to the temperature control of a batch-dyeing machine. Even though it is difficult to implement and tune the GPC in some controllers which have only limited mathematical computation ability, the GPC control law can be directly connected to the process parameters with some basic polynomials functions since a wide class of industrial processes, including the dyeing process, can be modelled approximately with few parameters.

In [17], an improvement by use of PID controller in dyeing and weaving hot water temperature control system response is presented. The dynamic model of a hot water temperature control system was obtained and a robust PID controller was designed using the PID tuner of the Matlab software. It is found that the PID controller was able to improve the transient response performance of the system in terms of rise time of 0.415 seconds, settling time of 2.49 seconds, and overshoot of 8.78%.

1.4. Motivation of the Thesis

Having sufficiently accurate reference tracking in the temperature control of textile processes is crucial to being able to obtain the desired product specifications. Currently, temperature control in the textile industry is usually carried out by simple control methods like PID control. Controller parameters of such methods are typically designated by field experts during the setup of the corresponding machine. Most of the time, these parameters remain unchanged. However, the textile environment is extremely dynamic, and control characteristics of processes change frequently. Due to this phenomenon, current control methods give inaccurate reference tracking performances in the long run. Therefore, it is necessary to develop algorithms that are adaptive to the dynamic nature of textile processes.

Developing and applying new algorithms for a real process that runs in an actual industrial site is a hard and time-consuming procedure compared to working in a simulation environment. The implementation of a newly developed algorithm to a real process can even take up to several weeks due to reasons like converting the algorithm into corresponding device software or having a proper factory environment that allows testing on machines with required permissions from factory management. At the same time, safety is one of the major concerns in industrial areas. To assure that no safety issues will be encountered during testing, all potential safety risks must be addressed prior to testing a newly developed algorithm.

In order to speed up algorithm development procedures, a simulation environment including process models should be prepared. By using these models and the simulation environment, algorithms can be developed and tested expeditiously and final versions of these algorithms suitable for field tests can be employed on real processes. By using this approach, safety is also ensured because algorithms that have the potential to harm the real-world processes can be detected in advance and necessary adjustments can be made before it is too late.

As mentioned in Section 1.3, there are various studies available in the literature. Although somehow related to modelling and developing adaptive control algorithms for textile processes, these studies are not focused on corresponding textile operations which involve the temperature control in drying and dyeing, while this study specifically focuses on these processes. Due to the lack of research on the matter in the literature, this study involves high novelty and will contribute to the literature significantly.

1.5. Organization of the Thesis

The organization of the rest of the thesis is as follows:

In Chapter 2, general concepts in textile processes are overviewed. Firstly, characteristics of drying and dyeing processes are introduced. Then, the structure and algorithms that are currently used to control the temperature in drying and dyeing processes are presented. Lastly, the controller performance assessment procedure for the applied controls is explained in detail.

In Chapter 3, the modelling procedure of the temperature in textile processes is presented. To start with, the characteristics of temperature in drying and dyeing processes are introduced by studying the relevant thermodynamic laws and reviewing related literature. Subsequently, unique system models are built and model parameters are identified for various drying and dyeing processes by utilising several parameter identification methods that are introduced.

In Chapter 4, the development and application of the Model Predictive Control (MPC) are introduced. At first, the fundamentals of the MPC are demonstrated. After that, the design procedure of the MPC is described. Finally, the process models are simulated by using the developed MPC algorithms.

In Chapter 5, Adaptive PI control and Error Predictive Control (EPC) are introduced. In the beginning, details of Adaptive PI control are explained by introducing the PI tuning methods which can be found in the literature and are developed in the scope of this thesis. Then, their application results are presented. Lastly, the development procedure of EPC is explained and application results of it are provided.

In Chapter 6, the thesis is concluded with a brief summary and future recommendations.

2. OVERVIEW OF GENERAL CONCEPTS IN TEXTILE PROCESSES

It is vital to introduce general concepts of the aforementioned textile processes in order to fully comprehend them before presenting modelling and developing control algorithms. These concepts are divided into three parts; process characteristics, currently used control and control performance assessment. First of all, characteristics of drying and dyeing processes will be introduced by also providing some theoretical background. Afterwards, the structure and algorithms that are used currently to control the temperature in drying and dyeing processes will be presented. Finally, the controller performance assessment procedure for the controls that are applied will be explained in detail.

2.1. Process Characteristics

In this section, the process characteristics of temperature in drying and dyeing processes will be introduced by examining the corresponding thermodynamic laws and real data from factories that apply these processes across their whole textile processes.

According to the corresponding thermodynamic laws, heat transfer is performed between two systems that permit heat transfer in a manner that would allow the heat to be transferred from the high temperature system to the low temperature system. Heat transfer process continues until the temperature difference between the two systems becomes zero. In heat transfer processes that include gases and mass transfer, the pressure of the systems affects mass transfer during evaporation. Mathematical equations describing corresponding thermodynamic laws are given as

$$\frac{\mathrm{d}Q(t)}{\mathrm{d}t} = \overline{h}A_t(T_A - T_t), \tag{2.1a}$$

$$\dot{m}_{ev}(t) = \overline{h}_m A_t(p_t - p_A), \tag{2.1b}$$

where Q is transferred heat, $\overline{h}$ is average heat transfer coefficient, A_t is surface area of the material, T_t is surface temperature of the material, T_A is air temperature, $\dot{m}_{ev}$ is mass transfer per second, $\overline{h}_m$ is mass transfer coefficient, p_t is surface pressure and p_A is air pressure. Equations (2.1a) and (2.1b) are the main equations that drive the drying processes and constitute their characteristic features.

2.1.1. Temperature in Drying Processes

In the analysis of data acquired from the actual drying processes, similar characteristics to those proposed by Brunzell in Figure 1.5 are achieved. Proposed drying characteristics for the temperature of a drying process are given in Figure 2.1. Temperature increases rapidly until heating reaches a certain point at which the increase in temperature becomes slower. The reason for this phenomenon is intense evaporation.

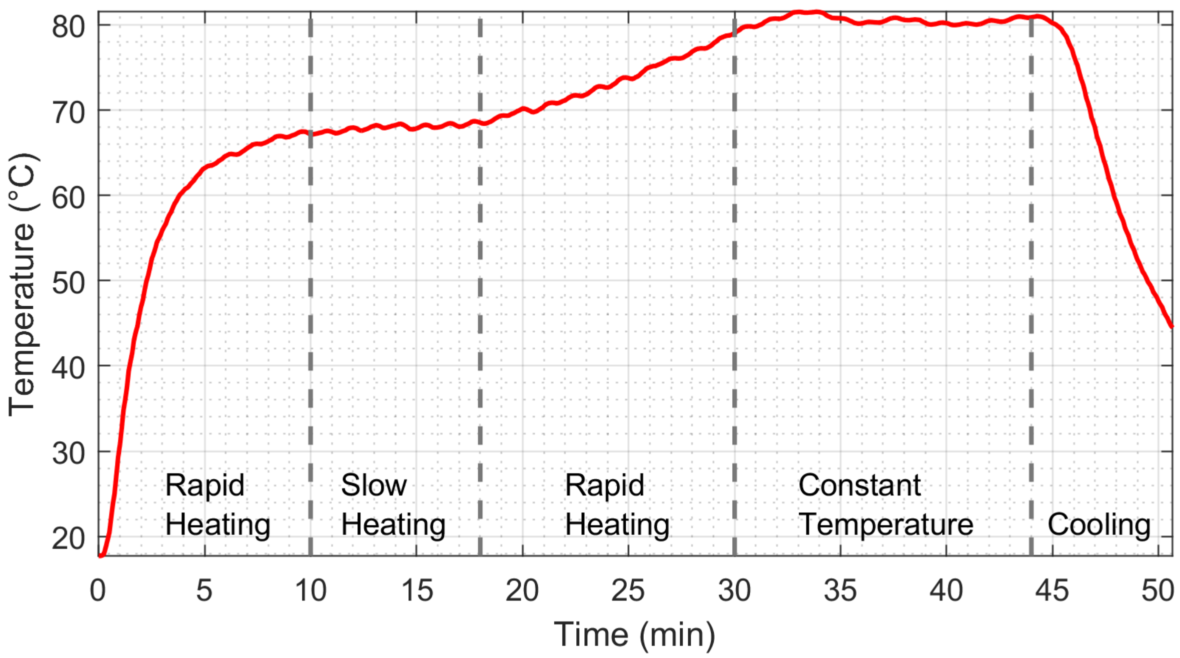


Figure 2.1. Temperature characteristics of a drying process.

As corresponding thermodynamic laws state, there will be no change in temperature during phase transition since all of the transferred heat is used for phase transition. Evaporation slows down as phase transition finishes and temperature starts to increase rapidly again. As the desired temperature level is reached, temperature is kept stable for a while until the desired dryness and shrinkage are achieved by using a controller. In the end, after a short cooling period, the process finishes. Even though temperature graphs differ between distinct processes due to the change in system inputs like mass and humidity of the material, temperature maintains its fundamental characteristics. This differentiation will be observed as the model parameters are determined for various types of processes.

2.1.2. Temperature in Dyeing Processes

As stated earlier, the temperature of the dye liquid, inside which the corresponding fabric is placed, is controlled throughout the dyeing process. This dye liquid is a composition of various chemicals such as water, dye, salt, caustic soda, carbonate etc. [6]. The temperature of this dye liquid is regulated through an exchanger mechanism that uses steam for heating and cold water for cooling. Characteristic of dye liquid temperature is also governed by (2.1a) and (2.1b).

The process characteristics obtained after analysing real data from corresponding factories are shown in Figure 2.2. At first, temperature increases rapidly for a short while. Then, temperature increases almost linearly for a longer period until the desired temperature is reached. Starting from that moment, temperature is controlled until dyeing finishes for this cycle. When the corresponding dyeing cycle finishes, temperature is decreased to a certain level and the dyeing process proceeds to the next cycle. Similar to heating, the cooling process also has two parts, as rapid cooling and linear cooling. In dyeing processes, which can last up to 24 hours, various temperature controls that have different setpoints, durations, input fabrics etc. are applied.

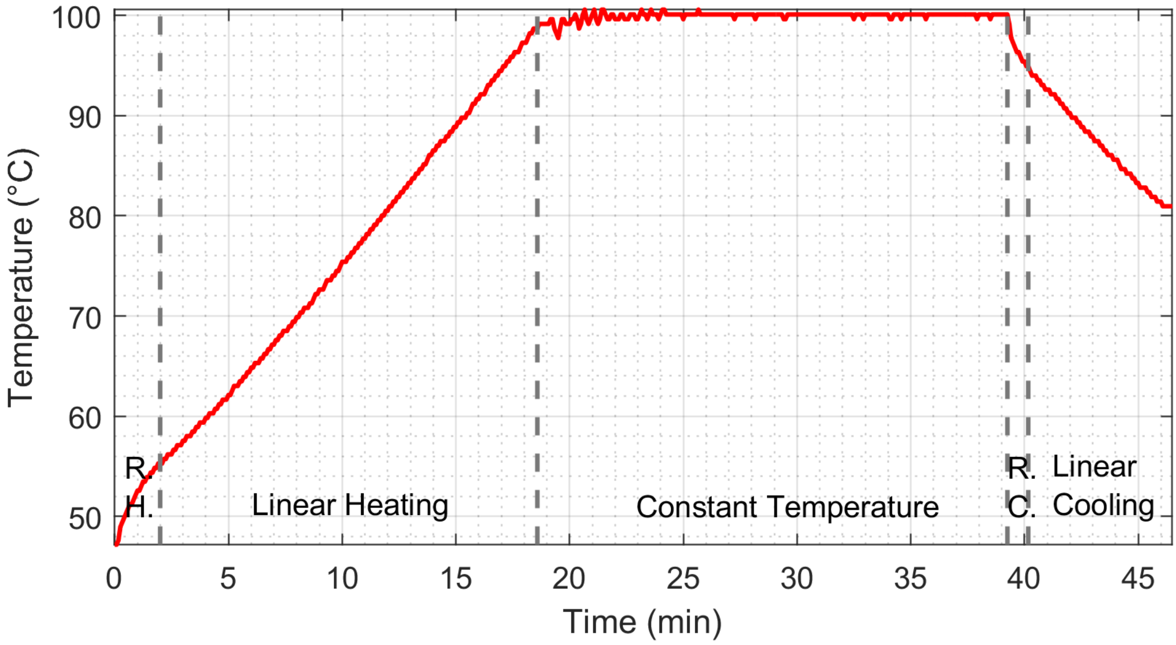


Figure 2.2. Temperature characteristics of a dyeing process. (R.H.: Rapid Heating, R.C.: Rapid Cooling)

2.2. Currently Used Control Algorithms

It is beneficial to understand the control algorithms that are used to govern a system, before developing these very control algorithms or completely new control algorithms for the corresponding system. In this way, not only the details of current control algorithms will be comprehended but also the system outputs obtained by using these control algorithms will be interpreted more consistently. It is also important to inspect the other factors that affect the control directly or indirectly. The most essential of these factors are valve and sensor dynamics. In this section, control algorithms currently in use will be introduced. Afterwards, valve, sensor and other process dynamics and their effects on control will be examined. Lastly, some examples of real process outputs will be shown.

2.2.1. Control Approach

The control approach that is currently used in corresponding systems is the PI (Proportional-Integral) approach. PI and PID (Proportional-Integral-Derivative) controllers are widely used in industrial applications. Some researches state that 95% of process control applications involve PI or PID controller [18]. Despite their wide use, it is observed that they are still unable to deliver satisfactory performances in certain situations. In a research that includes one hundred and fifty thousand control loops from over two hundred and fifty industrial areas, it is stated that 68% of these controllers exhibit unacceptable performances [19]. In another research, it is found that 75% of PID based control loops are not tuned properly [20]. In Figure 2.3, control loop that involves the PI controller is shown. In this loop, K_p and T_i represent the proportional gain and the integral time parameters of the PI controller, respectively. This control loop summarizes whole control schemes and controlled systems.

The error value that is obtained by taking the difference between the setpoint and the system output is used as the input of the PI controller. The PI controller output that passes through the valve dynamic constitutes the system input and an output is obtained by applying this input to the system.

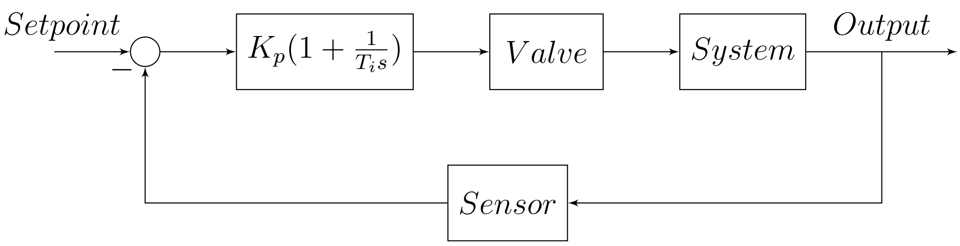


Figure 2.3. Control loop with the PI controller.

2.2.2. Valve Dynamics

Even though the corresponding systems are controlled by PI controllers, valve dynamics also affect these applied controls. Due to their mechanical nature, valves cause physical constraints. There are two types of valves that are currently used. These valve types are ON/OFF valves and Proportional valves. ON/OFF valves, which have two types of outputs, can be either ON or OFF throughout the whole process. This feature results in significant control restrictions. Proportional valves, on the hand, can give outputs as percentages. To compare, while ON/OFF valves can only give 0% or 100% outputs, proportional valves can give intermediate outputs like 50% or 75%. This makes proportional valves more flexible than ON/ OFF valves. At the same time, this flexibility depends on the resolution of the proportional valve. A proportional valve that provides more continuous outputs (higher resolution) will have a more sensitive output than a proportional valve that gives less continuous (lower resolution) outputs.

2.2.3. Sensor Dynamics

One of the most crucial components of closed-loop control is the sensors. To be able to feed the system output back to the controller, a suitable sensor is needed. On the other hand, because of their mechanical electrical structure, sensors bring along certain situations which affect the control. One such main situation is the resolution of the analog sensors. In theory, analog sensors can collect continuous value. However, in practice, it is not possible. Depending on its quality, a sensor's resolution changes. By analysing data sheets of the sensors, which are used in corresponding textile processes to read values like temperature, pressure and flow, it is revealed that in dyeing processes, sensor resolution is 0.46 °C and in drying processes, sensor resolution is 0.01 °C. It means that the difference between the two system output values can take integer multiples of 0.46 °C and 0.01 °C for dyeing and drying processes, respectively.

As in valve dynamics, there is also some delay in sensor dynamics due to their physical nature. Delay is different depending on the sensor type and it affects the control. At the same time, in large scale processes like corresponding textile processes, the physical placement of the sensors affects the reading of the sensors, thus affecting the control.

2.2.4. Filter Dynamics

The measurement noise is one of the problems in practical control applications. These measurement noises, which are caused because of the nature of sensors or by environmental factors, make it harder to have decent control. One of the primary solutions to this problem is applying filters to measurements of the sensors. Filters are mainly based on applying some mathematical manipulations to the measurements to make them run more silent. Some of the noise cancelling filters are moving average filters and low pass filters.

The main handicap of using filters is the delay that is added to the control loop. Due to the structure of filters, they use past measurements which do not properly reflect new measurements. So, it can be said that there is a trade-off between noise and delay. Process, sensor and filter dynamics as well as their effects on the control should be taken into consideration by the designer and the corresponding parameters, such as the filter coefficient, should be determined in an optimal manner. Some filter applications are compared in Figure 2.4. Noise cancelling and delay characteristics of different filters can be seen when the graphics are examined. Details of the filters are given as follows:

- No filter: A filter is not used, measurements are directly read from sensors with a 0.46 °C resolution.
- PLC filter: Mean of a certain number of past measurements is used while excluding outliers (highest and lowest measurements). The filter coefficient, which is a design parameter, determines how many last measurements will be used. The acquired value after this filter has an 8-bit structure and still needs calibration (measurements turn into real temperature values after calibration).

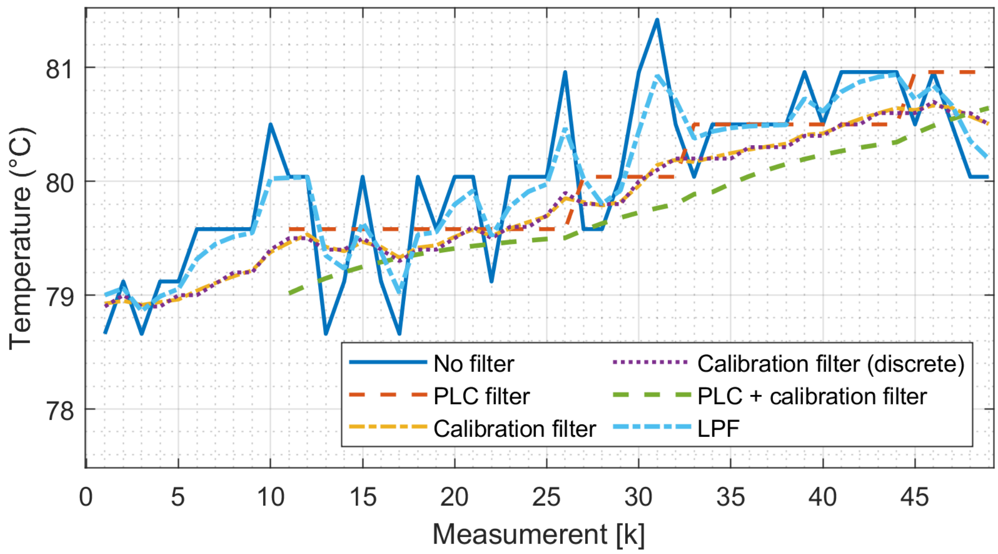


Figure 2.4. Comparison of different filters | PLC filter coefficient = 10, calibration filter coefficient = 8, calibration discreteness resolution = 0.1 °C, LPF degree = 1, LPF weight coefficient = 0.5.

- Calibration filter: Mean of a certain number of past calibrated measurements is used. The filter coefficient determines how many last measurements will be used. It gives continuous value thanks to its float characteristic. By using the other design parameter, which is the resolution coefficient, filter outputs can have the desired resolution (the corresponding value is rounded to the nearest resolution value).
- LPF: Weighted mean of a certain number of past measurements is used. Design parameters are filter degree and weight coefficient. The mathematical equation of a first degree LPF is given as

$$\overline{y}[k] = (1-\alpha)y[k-1] + \alpha y[k], \tag{2.2}$$

where k represents discrete measurement time, y represents the value that is read by the sensor, $\overline{y}$ represents filtered value and α represents weight coefficient. α takes values between 0 and 1. The weight of the last measurement increases as

α becomes close to 1.

PLC filter is used in current processes. In this study, different filters will be utilised and the best filter structures will be determined and worked with afterwards.

2.2.5. Other Dynamics

As well as valve and sensor dynamics, other external dynamics can affect the control. Some of them are: the type of the operating system and its qualities on which controller algorithm and software work, working period of the corresponding software (in corresponding textile processes, working periods are 0.05 and 1 seconds for drying and dyeing processes, respectively), the structure of electronic circuits which carry the control signals and the design of the Programmable Logic Controller (PLC) that communicates the control input and outputs with the physical system. Even though the effects of these dynamics are negligible, it is nonetheless necessary sometimes to take them into account.

2.2.6. Examples of Problematic Processes

When processes controlled by a PI controller are examined, some issues are detected. The need for improvements in the applied control became evident in view of these problematic processes. The improvements can be done not only by changing the structure of parameters of the currently used PI controller but also by developing new control algorithms. Problematic temperature control in a drying process is displayed in Figure 2.5.

Overshoots and sustained oscillations, which are unacceptable for drying processes, can be observed. The main reason for these problems in this particular process is using the wrong parameters for the PI controller. The problems can be fixed by choosing different PI controller parameters.

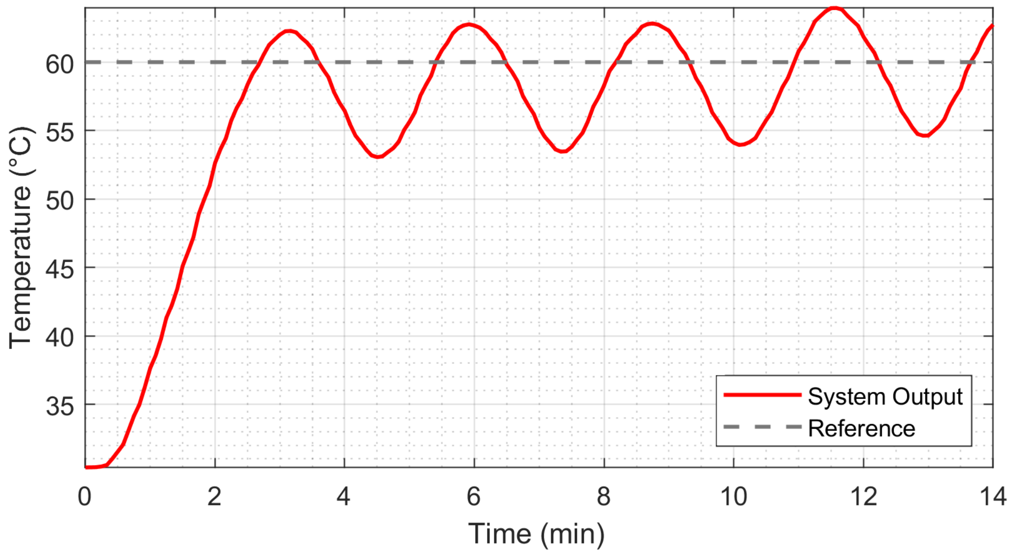


Figure 2.5. A problematic drying process temperature control that is controlled by a PI controller.

However, choosing different PI controller parameters may be insufficient in some processes. Making PI controller parameters adaptive to process dynamics or using entirely different control algorithms can be considered to overcome such a persistent problem.

Nowadays, PI controller parameters are determined by field experts. Field experts primarily use their own experiences while determining PI controller parameters. Usually, parameters are used without any change for long periods. Due to this fact, the PI controller cannot adapt to changing processes and environmental dynamics. This phenomenon causes degradation in control over time. Although utilising field experts again can be a solution to this problem, it is neither a fast nor a cost-effective remedy. A proper solution to this problem would be automatically updating PI controller parameters both offline and in real-time, which can be realized by utilising self-learning algorithms. Nevertheless, tuning PI controller parameters in the right way may not be the solution in every case due to the aforementioned process dynamics which can affect the control temporarily.

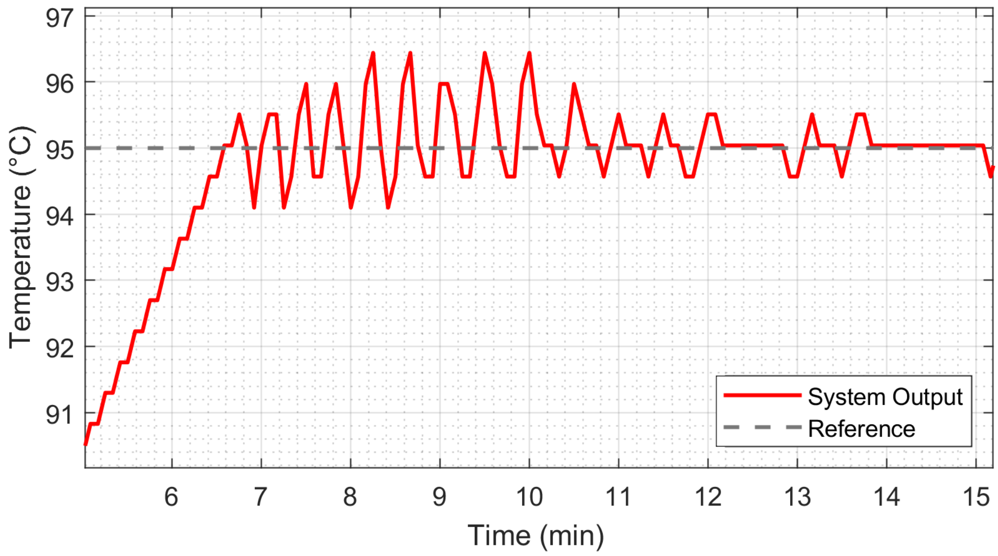


Figure 2.6. A problematic dyeing process temperature control that is controlled by a PI controller.

Problematic temperature control in a dyeing process is shown in Figure 2.6. The first thing that can be inferred when examining the graph is that temperature takes discrete values. The reason for this situation is the previously mentioned sensor resolution phenomenon. Temporary oscillations stand out when process outputs between the seventh and eleventh minutes are inspected. This type of damped oscillations are caused by the number and locations of the corresponding temperature sensors. When the temperature of a liquid with a huge volume is measured by only using one sensor, only the temperature of that specific part of the liquid is being measured. On the other hand, it is inevitable that temperatures of different parts of an item with high volume may differ significantly, especially in the transient part of the control. After reaching the reference temperature, heating is slowly decreased and the temperature of the whole liquid becomes homogenized. It takes a couple of minutes for a dyeing liquid, which is simultaneously circulated by a pump, to become completely homogenized for temperature. When the temperature is homogenized, control becomes uncomplicated. The phenomenon causing some problems in control can be resolved by increasing the number of sensors and utilising proper filters.

2.3. Controller Performance Assessment

Another vital aspect of developing control algorithms is the assessment of the performances of the proposed control algorithms. To be able to understand the success of the control that is applied and compare different control algorithms, a controller performance assessment procedure is necessary. While making a controller performance assessment, several statistical metrics, indices and rules can be utilised. First off in this section, statistical metrics will be introduced. Followingly, Harris Index and a performance assessment metric which is developed exclusively for the corresponding textile processes will be introduced.

2.3.1. Statistical Metrics

The process outputs, gathered after using a specific controller, have several statistical metrics like mean and variance. Some of these metrics and their calculation methods are as follows:

(i) Mean:

$$y_{mean} = \frac{1}{n}\sum_{i=1}^{n} y_i. \tag{2.3}$$

(ii) Variance:

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_{mean})^2. \tag{2.4}$$

(iii) Standard Deviation:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_{mean})^2}. \tag{2.5}$$

(iv) Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - SP|. \tag{2.6}$$

(v) Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - SP)^2. \tag{2.7}$$

(vi) Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - SP)^2}. \tag{2.8}$$

(vii) R-Squared (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - SP)^2}{\sum_{i=1}^{n}(y_i - y_{mean})^2}, \tag{2.9}$$

where y represents the controller output, i represents the controller output index, n represents the total number of the controller output and SP represents the reference (set point) value.

2.3.2. Harris Index

The Harris Index is a controller performance assessment index that was proposed by Thomas J. Harris in 1989 and it is based on the minimum variance control principle [21]. Minimum variance control (MVC) was first developed by Åstrom in 1970 [22]. The main principle of MVC based indices is comparing the performance of the real process with the maximum reachable performance for the processes that have time delay as the main limiting factor. Because of this fact, if the main limiting factor of a process is the time delay, the Harris Index gives satisfactory results [23]. In the corresponding textile processes, the time delay is one of the main limiting factors. Therefore, the Harris Index will give consistent results for controller performance assessment. Harris

Index is identified as follows

$$\eta_{MV} = \frac{\sigma^2_{MV}}{\sigma^2_y}, \tag{2.10}$$

where σ^2_{MV} represents the variance that will be obtained if MVC is applied to the corresponding process and σ^2_y represents the variance of the real process output. It can easily be seen that the index will be in [0,1] range. An index value closer to 1 means better controller performance. Another advantage of using the Harris Index is the fact that it only utilises the following process information regardless of the controller [24]:

- Closed-loop response outputs for the controlled variable
- Known or predicted system delay

There are several Harris Index calculation methods which can be found in the literature. In this work, Direct Least Squares Prediction algorithm proposed by Jelali is used for Harris Index calculations. Progress of the proposed algorithm is given as follows [24]:

(i) Under the assumption of closed-loop stability, process output is fit by using finite-length Autoregressive (AR) model:

$$y(k) = \sum_{i=1}^{n} \Theta_i y(k - \tau - i + 1) + E_\tau(q)\epsilon(k). \tag{2.11}$$

(ii) Similar terms are put together for certain k value:

$$\boldsymbol{y} = \boldsymbol{X\Theta} + E_\tau(q)\epsilon(k), \tag{2.12}$$

where $\boldsymbol{y} = \begin{bmatrix} y(N) \\ y(N-1) \\ \vdots \\ y(n+\tau) \end{bmatrix}$, $\boldsymbol{\Theta} = \begin{bmatrix} \Theta_1 \\ \Theta_2 \\ \vdots \\ \Theta_n \end{bmatrix}$ and

$$\boldsymbol{X} = \begin{bmatrix} y(N-\tau) & y(N-\tau-1) & \dots & y(N-\tau-n+1) \\ y(N-\tau-1) & y(N-\tau-2) & \dots & y(N-\tau-n) \\ \vdots & \vdots & \dots & \vdots \\ y(n) & y(n-1) & \dots & y(1) \end{bmatrix}.$$

(iii) $\boldsymbol{\Theta}$ is calculated by using least squares method:

$$\boldsymbol{\Theta} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y}. \tag{2.13}$$

(iv) Minimum and real variances are calculated:

$$\overline{\sigma}^2_{MV} = \frac{1}{N-\tau-2n+1}(\boldsymbol{y}-\boldsymbol{X\Theta})^T(\boldsymbol{y}-\boldsymbol{X\Theta}), \tag{2.14a}$$

$$\overline{\sigma}^2_{y} = \frac{1}{N-\tau-n+1}\boldsymbol{y}^T\boldsymbol{y}. \tag{2.14b}$$

(v) The Harris Index is calculated by proportioning minimum and real variances:

$$\overline{\eta}_{MV}(\tau) = \frac{\overline{\sigma}^2_{MV}}{\overline{\sigma}^2_{y}}. \tag{2.15}$$

In these equations, y represents the real process output, k represents the real process output discrete time index, τ represents the time delay, n represents the model order, i represents the model order index, Θ represents the model parameters, $E(q)$ and ϵ represents the disturbance data and N represents the total number of real process output. By using several real process outputs, the Harris Index values will be calculated and controller performance assessments will be completed.

2.3.3. Exclusive Performance Metric

Even though several statistical measures and indices have already been created to be used in controller performance evaluation, it might be necessary to develop some exclusive metrics which are designed based upon the features of the corresponding processes. Consequently in this work, a performance metric is specifically designed for the corresponding textile processes established on their process and measurement characteristics. This metric contributes to controller performance assessment procedures not only by being practical to calculate, but also by being able to be easily analysed. The proposed metric, which gives a successful performance in percentage, is given below as

$$S = 100 \times \left(1 - \frac{\sum E_{OSR}^2}{N_T}\right), \tag{2.16}$$

where N_T represents the total number of measurements and E_{OSR} represents the errors of th measurements compared to the reference value outside of the success region. The success region in this work is defined as the region between -0.5 °C below and 1.0 °C above of the reference value.

2.4. Summary of the Chapter

In this chapter, general concepts in textile processes have been overviewed. Firstly, process characteristics of the temperature in drying and dyeing processes have been introduced. Then, control algorithms in current use have been presented, together with control approach and control dynamics, as well as some problematic process examples. Lastly, some statistical metrics, an index and a performance metric for controller performance assessments have been shared. These concepts will be helpful for understanding the process and control characteristics of the corresponding processes and some of them will later be utilised in Chapter 3 over the course of modelling and in Chapters 4-5 while developing control algorithms.

3. MODELLING OF TEXTILE PROCESSES

As stated earlier, drying and dyeing processes are textile processes that will be modelled in the scope of this thesis and temperature will be the system variable that will be modelled. First of all, by investigating the corresponding thermodynamic laws and examining the related literature, the characteristics of temperature in drying and dyeing processes will be introduced. Afterwards, unique system models will be built and model parameters will be identified for various drying and dyeing processes, by using a number of parameter identification methods which will be introduced later.

3.1. Model Structure

In this section, model structures of the temperature in drying and dyeing processes will be built by using corresponding thermodynamic laws and proposed process characteristics. By examining (2.1a), the conclusion can be drawn that it is a first order differential equation. This means that temperature can be modelled by using a first order model. By adding a delay factor, which is a necessary phenomenon to model real-life applications, a first order plus dead time model is obtained. The proposed model is described by

$$H_1(s) = e^{-\tau s}\frac{a}{s+b}, \tag{3.1}$$

where τ is the time delay, a is the system gain and b is the time constant. A second order model that is obtained by approximating time delay in (3.1) as a first order model given as

$$H_2(s) = \frac{1}{\tau s+1}\frac{a}{s+b}. \tag{3.2}$$

A second order plus dead time model is proposed to use when it is not sufficient to use the first order model as

$$H_3(s) = e^{-\tau s}\left(\frac{a_1}{s+b_1} + \frac{a_2}{s+b_2}\right). \tag{3.3}$$

Equation (3.3) is constructed by assembling two first order models and adding a delay factor. This model has 2 different system gains as a_1 and a_2, 2 different time constants as b_1 and b_2 and a time delay as τ. For modelling the processes with higher order characteristics, the second order model will be more advantageous. On the other hand, due to having a larger quantity of parameters, it will be harder to calculate the parameters of the higher order models.

3.1.1. Temperature in Drying Processes

Each of the temperature regions that is shown in Figure 2.1 will be modelled separately by using one of the proper models that are given in (3.1), (3.2) and (3.3). As previously mentioned, the temperature in drying processes additionally has oscillatory characteristics due to drum dynamics, sensor dynamics and homogenization of temperature. To be able to model this phenomenon, a sinusoidal model is proposed as

$$H_4(s) = \frac{a}{s^2+b^2}, \tag{3.4}$$

where a represents the oscillation amplitude and b represents the oscillation period. This model will be included in the models of all temperature regions. After analysing a significant number of actual drying processes, a complete model for drying processes is built and presented as

$$H_5(s) = \begin{cases} e^{-\tau s}\dfrac{a_1}{s+b_1}, & \text{1st Rapid Heating} \\[2ex] \dfrac{a_2}{s+b_2}, & \text{Slow Heating} \\[2ex] \dfrac{a_3}{s+b_3} + \dfrac{a_4}{s+b_4}, & \begin{array}{l}\text{2nd Rapid Heating \&} \\ \text{Constant Temperature}\end{array} \end{cases} + \frac{a_5}{s^2+{b_5}^2}, \tag{3.5}$$

where τ, a_1 and b_1 are parameters of 1st rapid heating region; a_2 and b_2 are parameters of the slow heating region; a_3, b_3, a_4, and b_4 are parameters of 2nd rapid heating region; a_5 and b_5 are parameters of drum and sensor dynamics. External process effects such as input and output noise and measurement errors will be included later in the simulation environment. By using the proposed model and simulation environment with the real data, parameters of the model for different processes will be identified.

3.1.2. Temperature in Dyeing Processes

In the literature, first and second order plus dead time models, which are given in (3.1) and (3.3), are proposed for temperature variable in dyeing processes [13]. Although (3.1) can be employed for modelling rapid heating regions., it is not suitable for linear heating regions. Therefore, the model in (3.3) is used to model linear heating regions. The problem with this second order model is that it is not capable of modelling constant temperature regions due to the fact that this model is not necessarily designed to model controller behaviour. In order to overcome this issue, the model is modified in such a manner that its time constants depend on system input. The mentioned modification also alters the structure of the model to a nonlinear one. After analysing sufficient real data, a complete model structure is built for the temperature in dyeing processes that are given as

$$\dot{y}_i(t) = -\bar{b}_i y_i(t-\tau_i) + a_i u_i(t-\tau_i), \tag{3.6a}$$

$$\bar{b}_i(t) = b_i((1-\alpha_i)u(t) + \alpha_i), \tag{3.6b}$$

$$u_i(t) = \left(1 - \alpha_i \frac{T_{Machine}}{T_{Steam}}\right) u(t) + \alpha_i \frac{T_{Machine}}{T_{Steam}}, \tag{3.6c}$$

$$\tau_i(t) = \begin{cases} \tau_1, & i = 1,2,3, \\ \tau_2, & i = 4,5,6, \end{cases} \tag{3.6d}$$

$$y(t) = \begin{cases} y_1(t), & \text{Rapid Heating} \\ y_2(t) + y_3(t), & \text{Linear Heating \& Constant Temperature} \\ y_4(t), & \text{Rapid Cooling} \\ y_5(t) + y_6(t), & \text{Linear Cooling} \end{cases}, \tag{3.6e}$$

where t is time, u is the system input, y is the model output, $\dot{y}$ is the first derivative of y with respect to time; τ_1 and τ_2 are delay times of heating and cooling valves respectively; y_1, a_1 and b_1 are output and parameters of the rapid heating region; y_2, y_3, a_2, a_3, b_2, b_3, α_2 and α_3 are output and parameters of linear heating and constant temperature regions; y_4, a_4, b_4, and α_4 are output and parameters of the rapid cooling region; y_5, y_6, a_5, a_6, b_5, b_6, α_5 and α_6 are parameters of the linear cooling region; $T_{Machine}$ and T_{Steam} are machine and steam temperatures, respectively. Machine temperature is determined as 75° C and steam temperature is determined as 175° C; α_1 and α_2 are determined as 0; α_3 and α_4 are determined as 0.005; α_5 and α_6 are determined as 0.01 after analysing real process and machinery data. Input and output noise, sensor measurement error and dye liquid homogenization effect will be included in the simulation environment. By using constructed model and real data, model parameters will be identified for different types of processes.

3.2. Modelling Procedure

After constructing the process model and obtaining real process data, the following steps will be applied to complete the modelling procedure for the corresponding process. These steps are given as follows:

(i) Region Partitioning
(ii) Parameter Identification
(iii) Fit Rate Calculation

By applying these steps, each of the individual process will be modelled.

3.2.1. Region Partitioning

As aforesaid, drying and dyeing processes consist of various regions that have different characteristics and different model structures accordingly. Therefore, it is necessary to determine these regions before going into parameter identification procedures. Before starting to work on real data, it is essential to prepare corresponding data suitable for modelling. To achieve this, open-loop data is interpolated by using the spline method [25] as having T=1 second sampling period to be able to have sufficient precision for parameter identification.

Afterwards, open-loop data of the corresponding process will be fitted to the 5th order polynomial that is shown as

$$p(x) = a_1x^5 + a_2x^4 + a_3x^3 + a_4x^2 + a_5x + a_6, \tag{3.7}$$

where a_1, a_2, ..., a_6 represent coefficients of polynomial. Non-linear Nelder-Mead Simplex [26] and Interior Point [27] algorithms will be used for these fitting procedures. Region boundaries are detected by using extremum points of the first order derivative of (3.7). After several trials, first order derivative limits for drying and dyeing processes are determined as 0.005 and 0.075, respectively. An example of region partitioning for a drying process is displayed in Figure 3.1.

3.2.2. Parameter Identification

In this section, the temperature parameter identification procedure for different drying and dyeing processes will be introduced. First of all, the models that are in the Laplace domain will be transformed to the time domain by using inverse Laplace transform techniques. The parameters of these mathematical equations will be identified via the utilisation of specified curve fitting techniques and real data of the corresponding processes.

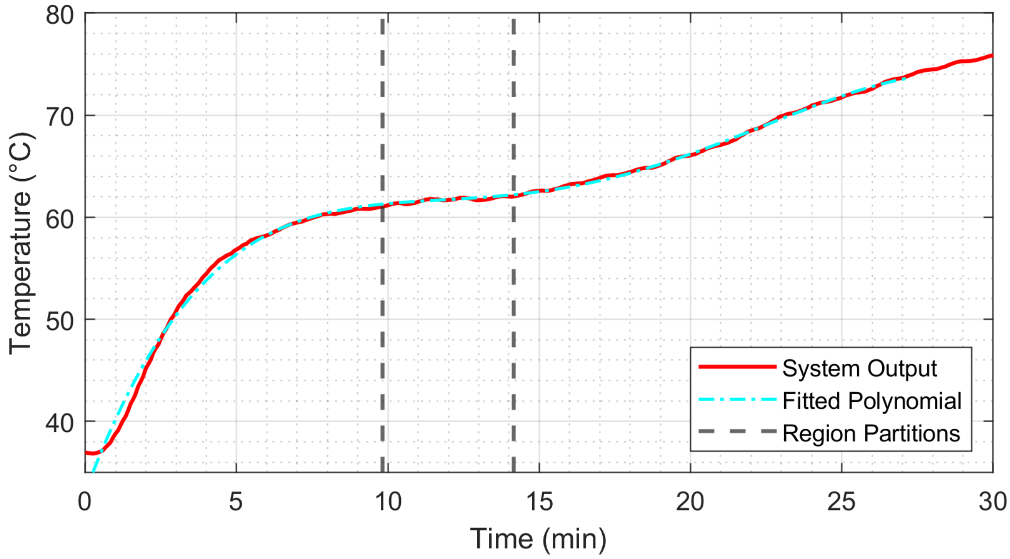


Figure 3.1. An example of region partitioning for a drying process.

The curve fitting technique which will be used in parameter identification is the least squares technique. Although the least squares technique which has a linear regression structure, is one of the simpler curve fitting techniques, it is sufficient and effective enough most of the time. The least squares technique is based on discrete time equations of the corresponding model. Due to the problems of acquiring discrete time equations of the second order model, the least squares will be used for identifying first order models. Discrete time equation of the step response of the model in (3.1) is shown as

$$y[k+1-\tau] = y[k-\tau] + T(-by[k-\tau] + au[k-\tau]), \tag{3.8}$$

where k is the discrete time index, τ is the time delay, T is the sampling period, u is the system input, which is a step input, y is the system output, a is the system gain and b is the system time constant. a and b parameters will be identified for each temperature region separately. The equations that will be used to identify these parameters are shown below as

$$A_L = T \begin{bmatrix} 1 & -y_0 \\ \vdots & \vdots \\ 1 & -y_{k-1} \end{bmatrix}, \tag{3.9a}$$

$$c_L = \begin{bmatrix} y_1 - y_0 \\ \vdots \\ y_k - y_{k-1} \end{bmatrix}, \tag{3.9b}$$

$$\widehat{x} = (A_L^T A_L)^{-1} A_L^T c_L = \begin{bmatrix} a & b \end{bmatrix}^T. \tag{3.9c}$$

3.2.3. Fit Rate Calculation

Following completion of the parameter identification procedure, the fit rate of the identified parameters will be calculated to understand how well these parameters model the corresponding process. The R-Square technique will be deployed to find the fitting rate. The equations that will be used to obtain the fitting rate are expressed as

$$\overline{y} = \frac{1}{n} \sum_{i=1}^{n} y_i, \tag{3.10a}$$

$$SS_{residue} = \sum_i (y_i - f_i)^2, \tag{3.10b}$$

$$SS_{total} = \sum_i (y_i - \overline{y})^2, \tag{3.10c}$$

$$R^2 = 1 - \frac{SS_{residue}}{SS_{total}}, \tag{3.10d}$$

where n is the total data sample number, y_i is the data at ith moment, $\overline{y}$ is the average data, f_i is the model data of ith moment and R^2 is the R-Square value. The fitting rate will be calculated as a percentage (R^2*100). In the end, the model will be simulated by using the identified parameters and the results will be compared with the real data. This process will be applied to various real data sets, which are obtained from distinct factories and machines that have different environmental conditions.

3.3. Examples of Modelling

In this section, several modelling examples for drying and dyeing processes will be presented including model parameters and fit rates. In Figure 3.2 and Figure 3.3, two different modelling examples for the drying process are displayed. Since drying processes are very dynamic, in such a way that every process has unique characteristics, it can be observed that model parameters differ as the process changes.

In Figure 3.4 and Figure 3.5, two different modelling examples for the dyeing process are shown. Similar to drying modelling, model parameters of dyeing models also differ as a result of the fluctuations in dyeing process dynamics.

3.4. Summary of the Chapter

This chapter has started with proposing model structures of the temperature in drying and dyeing processes by taking into consideration corresponding thermodynamic laws and process characteristics and has continued with modelling application procedures which include region partitioning, parameter identification and fit rate calculation. Modelling examples have also been added at the end of the chapter. Some of these modelling examples will be utilised in Chapters 4-5 while simulating developed control algorithms.

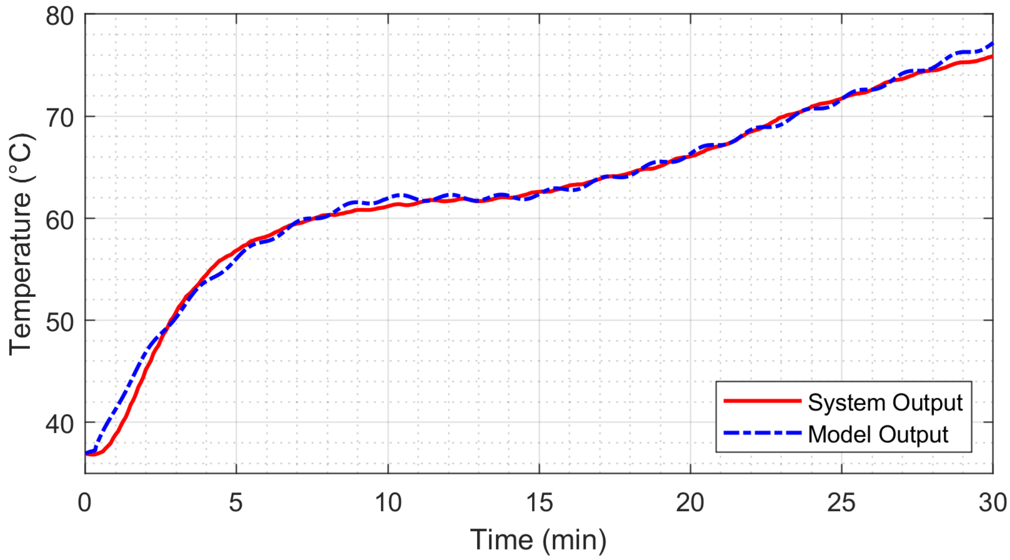


Figure 3.2. Drying process modelling | Example 1 | $\tau = 20$ sec, $a_1 = 0.2712$, $b_1 = 0.00421$, $a_2 = 0.6062$, $b_2 = 0.00977$, $a_3 = 0.0496$, $b_3 = 0.00036$, $a_4 = -0.0215$, $b_4 = 0.00304$, $a_5 = 0.0006$, $b_5 = 0.06283$, Fit Rate= 99.26%.

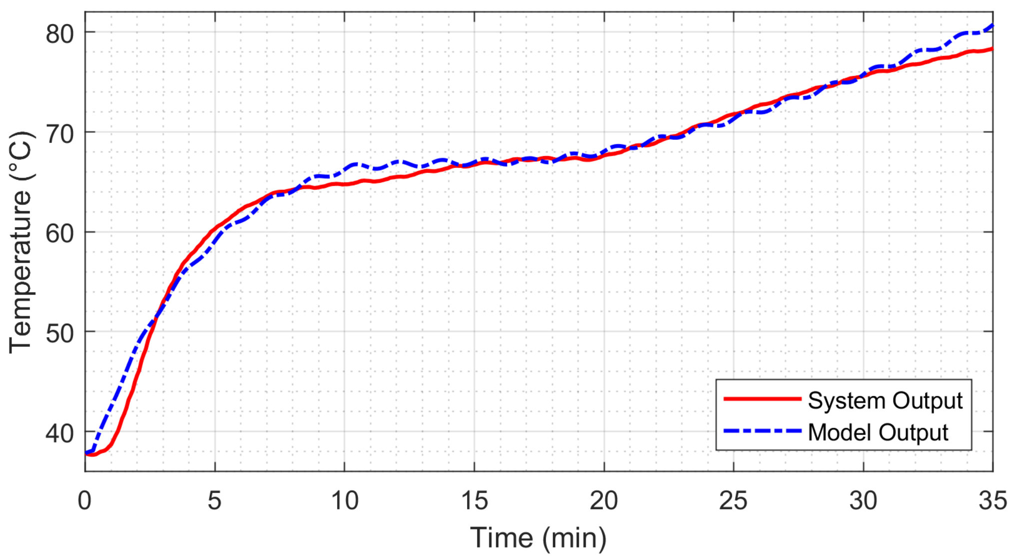


Figure 3.3. Drying process modelling | Example 2 | $\tau = 20$ sec, $a_1 = 0.2756$, $b_1 = 0.00397$, $a_2 = 0.3291$, $b_2 = 0.0049$, $a_3 = 0.123$, $b_3 = 0.00058$, $a_4 = -0.0809$, $b_4 = 0.00099$, $a_5 = 0.0006$, $b_5 = 0.06283$, Fit Rate= 98.5%.

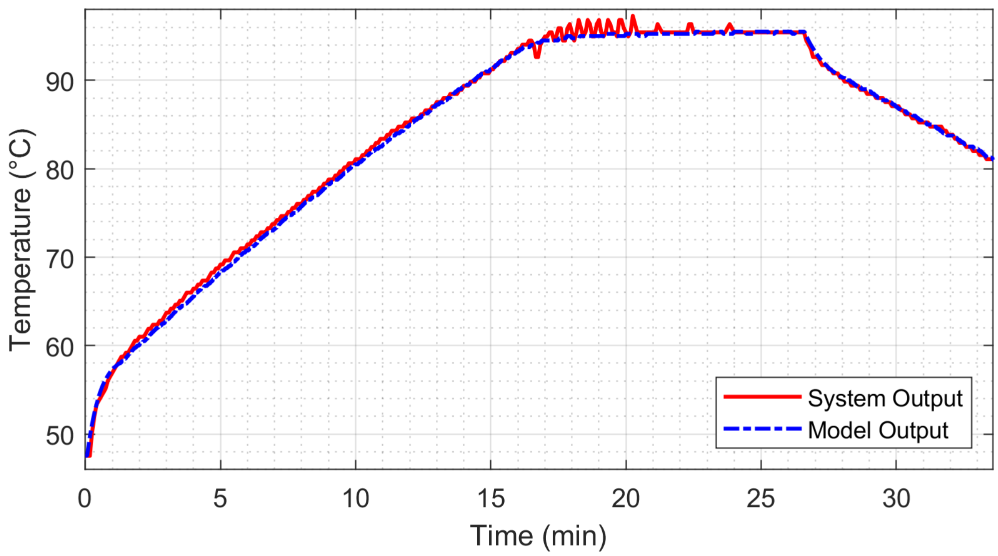


Figure 3.4. Dyeing process modelling | Example 1 | $\tau_1 = 4$ sec, $\tau_2 = 6$ sec, $a_1 = 1.4662$, $b_1 = 0.02388$, $a_2 = 0.1074$, $b_2 = 0.00039$, $a_3 = -0.0374$, $b_3 = 0.00038$, $a_4 = 1.4828$, $b_4 = 0.01671$, $a_5 = 0.1309$, $b_5 = 0.00109$, $a_6 = -0.0601$, $b_6 = 0.0006$, Fit Rate= 99.78%.

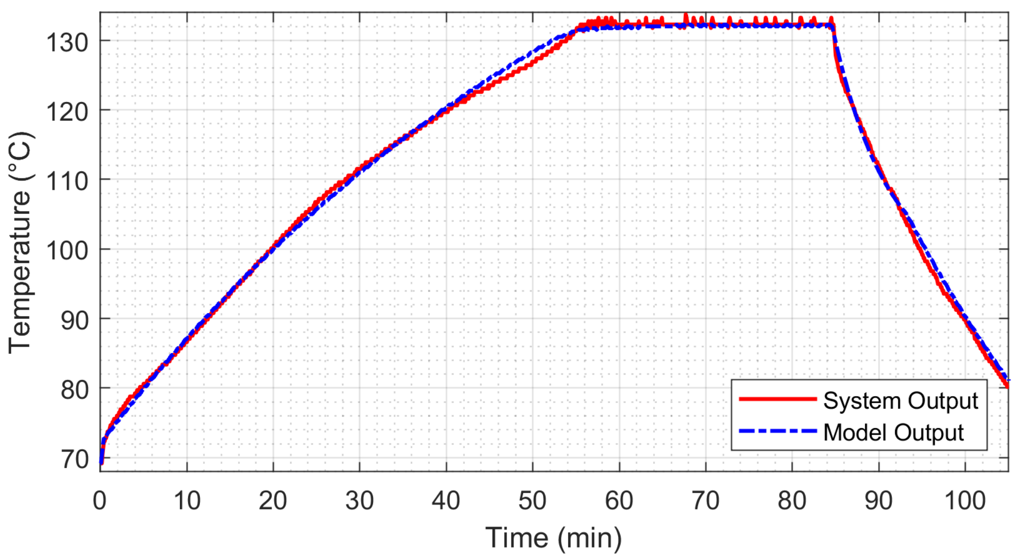


Figure 3.5. Dyeing process modelling | Example 2 | $\tau_1 = 4$ sec, $\tau_2 = 6$ sec, $a_1 = 2.1926$, $b_1 = 0.02894$, $a_2 = 0.0661$, $b_2 = 0.00025$, $a_3 = -0.0215$, $b_3 = 0.00024$, $a_4 = 0.2192$, $b_4 = 0.00235$, $a_5 = 0.0618$, $b_5 = 0.00051$, $a_6 = -0.0472$, $b_6 = 0.00047$, Fit Rate= 99.39%.

4. MODEL-BASED CONTROL ALGORITHMS

Model-based control algorithms are control algorithms that use a process model directly or indirectly to calculate the control input. In this chapter, the development and application of Model Predictive Control (MPC), which is one of the most common model-based control methods, will be presented in detail. First of all, the fundamentals of MPC will be introduced. Afterwards, the design procedure of MPC for the corresponding processes will be described. Finally, the process models will be simulated by using the developed MPC algorithms.

4.1. Fundamentals of MPC

Model Predictive Control (MPC) is an advanced control approach that is based on projecting the future behaviours of the corresponding process and applying a proper control input to the system according to these projections. Some researches state that MPC is more effective than the PID control [28]. Even though MPC may be more effective than the PID control, it is not as widely used in industrial applications due to reasons such as the requirement of the model of the controlled system, the difficulty of implementation procedures and the higher need for computational power.

A typical MPC consists of two main parts, which are the system model and the optimizer. The building blocks of a typical MPC are shown in Figure 4.1. The model block constitutes the mathematical model which represents the system that will be controlled. This model is used to predict the future behaviour of the system. The limit of this prediction is called the prediction horizon. The prediction horizon is one of the fundamental design parameters of MPC and it should be chosen to work compatibly with the system model. Conventional PID controllers do not have this kind of prediction characteristic; instead, they can only respond to the changes when the changes occur.

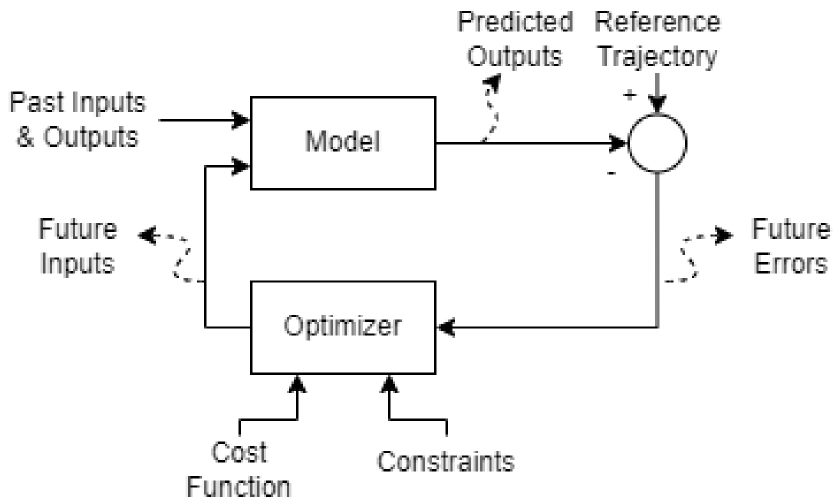


Figure 4.1. Building blocks of a typical MPC [29].

The optimizer is the block where the control input is calculated. Optimizer is based on some mathematical equations that are called cost functions and it uses both reference values and input-output constraints. Controllers that are based on the MPC approach are also compatible with Multiple Input Multiple Output (MIMO) systems and they are currently being used in chemical plants and petrol refineries [30]. This testifies that MPC is also suitable for textile processes that are studied in this thesis. Firstly, the theoretical structure of MPC will be examined and it will be designed in a simulation environment. The designed MPC will be simulated and verified by using the previously constructed system models. Then, the textile processes will be controlled by MPC and results will be analysed by means of proper performance metrics.

4.2. MPC Design

As mentioned before, MPC consists of two main parts which are the system model and the optimizer. MPC design is built on these two basic components. Firstly, the works about obtaining the system models and preparing the corresponding mathematical equations via utilisation of these very system models will be introduced. These models are prepared in a certain way, enabling MPC to use these models in its algorithms. Followingly, the works about designing the optimizer block, the cost functions and the input-output constraints will be presented.

4.2.1. MPC System Model

In the previous chapter, the system models have been prepared for the corresponding textile processes which will be used as system models in MPC. The only thing needed to be done is to prepare these models in such a way that MPC can use these models in its algorithms.

Prepared system models are either in the time domain or in the Laplace domain. Also, it was proposed that, depending on the process characteristics, different process regions may have different model structures and model parameters. It is known that MPC uses system models which are designed in state-space domain representation, the main structure of which is given as (all equations in this section can be found in [31], [32] and [33])

$$x[k+1] = Ax[k] + Bu[k], \tag{4.1a}$$

$$y[k] = Cx[k] + Du[k], \tag{4.1b}$$

where k represents the discrete time index, x, u and y represent the model state, the control input and the model output, respectively and A, B, C and D represent the state-space matrices. By using these matrices and equations, the system model outputs, which will be predicted by MPC, will be calculated.

The state-space matrices for the system models that are in the Laplace domain will be calculated by using the equations that are given as

$$H(s) = \frac{Y(s)}{U(s)} = \frac{b_0 s^n + b_1 s^{n-1} + ... + b_{n-1} s + b_n}{s^n + a_1 s^{n-1} + ... + a_{n-1} s + a_n}, \tag{4.2a}$$

$$A = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \\ -a_n & -a_{n-1} & -a_{n-2} & \dots & -a_1 \end{bmatrix}, \tag{4.2b}$$

$$B = \begin{bmatrix} 0 & 0 & \dots & 0 & 1 \end{bmatrix}^T, \tag{4.2c}$$

$$C = \begin{bmatrix} (b_n - a_n b_0) & \dots & (b_1 - a_1 b_0) \end{bmatrix}, \tag{4.2d}$$

$$D = b_0, \tag{4.2e}$$

where $H(s)$, $U(s)$, and $Y(s)$ represent the system model, the system input and the system output in the Laplace domain, respectively, n represents the degree of the system model, a and b represent the system model parameters. These equations will be used to calculate the state-space matrices given in (4.1) for the corresponding process region in real time. Through these state-space matrices, the system outputs will be estimated up to a specific prediction horizon that is determined by the designer while designing MPC.

The equations that predict the system outputs for an MPC design that has p as the prediction horizon are given as

$$\begin{bmatrix} y[k+1|k] \\ y[k+2|k] \\ \vdots \\ y[k+p|k] \end{bmatrix} = S_x x[k|k] + S_{u_1} u[k-1] + S_u \begin{bmatrix} u[k|k] \\ u[k+1|k] \\ \vdots \\ u[k+p-1] \end{bmatrix}, \tag{4.3a}$$

$$S_x = \begin{bmatrix} CA & CA^2 & \dots & CA^p \end{bmatrix}^T, \tag{4.3b}$$

$$S_{u_1} = \begin{bmatrix} CB_u & CB_u + CAB_u & \dots & \sum_{i=0}^{p-1} CA^i B_u \end{bmatrix}^T, \tag{4.3c}$$

$$S_u = \begin{bmatrix} CB_u & 0 & \dots & 0 \\ CB_u + CAB_u & CB_u & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=0}^{p-1} CA^i B_u & \sum_{i=0}^{p-2} CA^i B_u & \dots & CB_u \end{bmatrix}. \tag{4.3d}$$

4.2.2. Optimizer Block

The optimizer block collects the predicted system outputs that are predicted by the system model, and calculates optimum control inputs which are represented by c up to the prediction horizon. These calculations are repeated in every control step and only the first calculated optimum control output is applied to the real system. The cost function for this system can be represented as

$$J = \frac{1}{2} z^T \overline{H} z + \overline{f}^T z,$$

where z represents optimum control input, $\overline{H}$ and $\overline{f}$ represent optimization matrices. For each control step, the optimum control input is calculated as a result of the optimization problem, which is given as

$$\begin{aligned} &\underset{z}{\text{minimize}}\ J \\ &\text{subjected to } A_c z \leq b_c, \end{aligned}$$

where A_c and b_c represent constraint and cost matrices that are designed according to the aimed performance criteria and system constraints by the designer.

It is crucial to have some physical constraints due to the controlled system's physical structure. These constraints are mainly classified as input, input change and output constraints. When computing the optimum control inputs, the optimizer block takes these restrictions into account. Equations for constraints are given as

$$y_{min}[k] + \epsilon_k V^y_{min} \leq y[k] \leq y_{max}[k] + \epsilon_k V^y_{max}, \tag{4.4a}$$

$$u_{min}[k] + \epsilon_k V^u_{min} \leq u[k] \leq u_{max}[k] + \epsilon_k V^u_{max}, \tag{4.4b}$$

$$\Delta u_{min}[k] + \epsilon_k V^{\Delta u}_{min} \leq \Delta u[k] \leq \Delta u_{max}[k] + \epsilon_k V^{\Delta u}_{max}, \tag{4.4c}$$

where y, u and Δu represent the system output, the control input and the difference between the current control input and the previous control input, respectively, min and max represent the minimum and maximum values for the corresponding variable, respectively and ϵ and V represent the other constraint parameters. In these equations, minimum and maximum values of variables and parameter values are determined by the designer.

4 main control tasks constitute the cost function that is used while calculating optimum control inputs, which are given below as

- Output reference tracking
- Input reference tracking
- Input rate of change tracking
- Constraint violation tracking

The cost function for z_k control input, which is applied at time k, is given as

$$J(z_k) = J_y(z_k) + J_u(z_k) + J_{\Delta u}(z_k) + J_{\epsilon_k}(z_k). \tag{4.5}$$

Each separate cost function that represents different control tasks is calculated by weighted summing the squares of the difference between the reference values and predicted values. Weights for each control task are determined by the designer in accordance with the aimed control performance. Equations representing how the costs are calculated for the corresponding control task are given as

$$J_y(z_k) = \sum_{j=1}^{n_y}\sum_{i=1}^{p}[\omega_{ij}^{y}(r_{oj}[k+i|k] - y_j[k+i|k])]^2, \tag{4.6a}$$

$$J_u(z_k) = \sum_{j=1}^{n_u}\sum_{i=0}^{p-1}[\omega_{ij}^{u}(r_{ij}[k+i|k] - u_j[k+i|k])]^2, \tag{4.6b}$$

$$J_{\Delta u}(z_k) = \sum_{j=1}^{n_u}\sum_{i=0}^{p-1}[\omega_{ij}^{\Delta u}(u_j[k+i|k] - u_j[k+i-1|k])]^2, \tag{4.6c}$$

$$J_{\epsilon}(z_k) = \rho_{\epsilon}\epsilon_k^2, \tag{4.6d}$$

where r_i and r_o represent input and output reference values, respectively, w represents the weight of the corresponding control task, n_u and n_y represent the number of input and output, respectively, p represents the prediction horizon and ρ_{ϵ} represents the constraint violation coefficient. The sum of these costs gives the total cost of for the moment which is calculated by the optimizer block. The optimum control input, z_k, is calculated by using an algorithm called Quadratic Programming (QP). QP solves the optimization problem that is defined by the cost functions. Optimization matrices, $\overline{H}$ and $\overline{f}$, are shown as

$$H = S_u^T Q S_u + R, \tag{4.7a}$$

$$\overline{H} = \begin{bmatrix} 2H & 0 \\ 0 & 2\rho_{\epsilon} \end{bmatrix}, \tag{4.7b}$$

$$c_y = S_x x[k|k] + S_{u_1} u[k-1] - Y_{ref}, \tag{4.7c}$$

$$f^T = 2c_y^T Q c_y, \tag{4.7d}$$

$$\overline{f} = \begin{bmatrix} f & 0 \end{bmatrix}, \tag{4.7e}$$

where Q and R represent output and input change weights matrices, respectively and Y_{ref} represents the output reference value.

4.3. MPC Applications

In this section, simulation results of process models, which are controlled by a controller structure that is designed via the aforementioned MPC approach, will be presented. The application will be done on dyeing processes, and since the control is applied mainly in linear heating & constant temperature regions, only they will be taken into consideration. The corresponding models presented in Figure 3.4 and Figure 3.5 will be designed appropriately and MPC will utilise these models while making predictions. MPC will not be applied in the field to the real processes owing to the fact that implementing MPC into the real controllers is not possible at the moment because of device and software restrictions.

Set of MPC parameters and constraints that are used to design the MPC based controller is given in Table 4.1. Simulation results, which are obtained by applying the designed controller to the corresponding process models with control inputs, can be seen in Figure 4.2 and Figure 4.3.

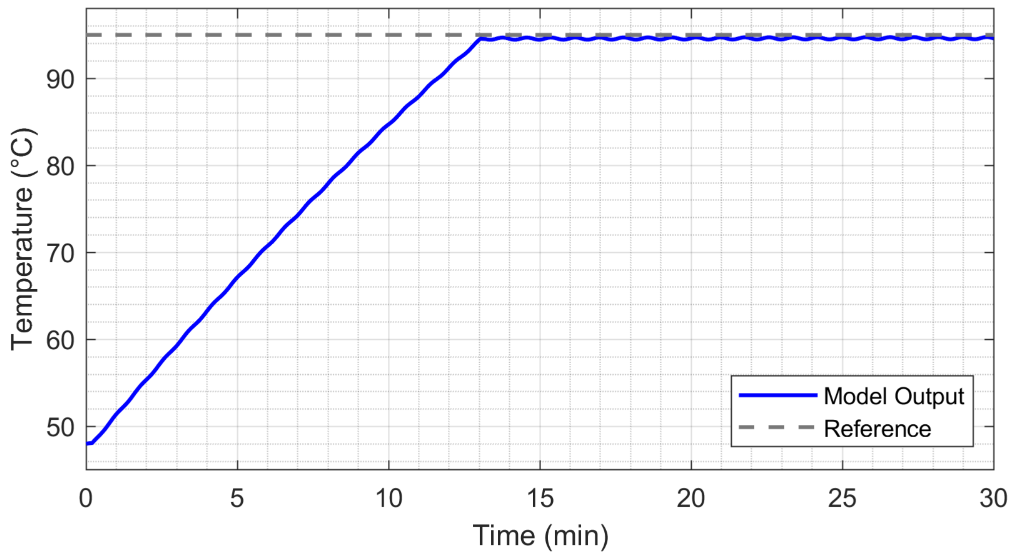
It can be seen that MPC successfully controls the corresponding processes. It predicts the outputs up to the given horizon and adjusts the control input accordingly. Even though MPC gives decent control performances in the simulation environment, it is hard to apply in real processes due to several problems like software implementation issues and high computational power requirements. Therefore, it's not worth implementing MPC in the real processes because similar control performances can be achieved by using much simpler controller structures.

Table 4.1. MPC parameters and constraints.

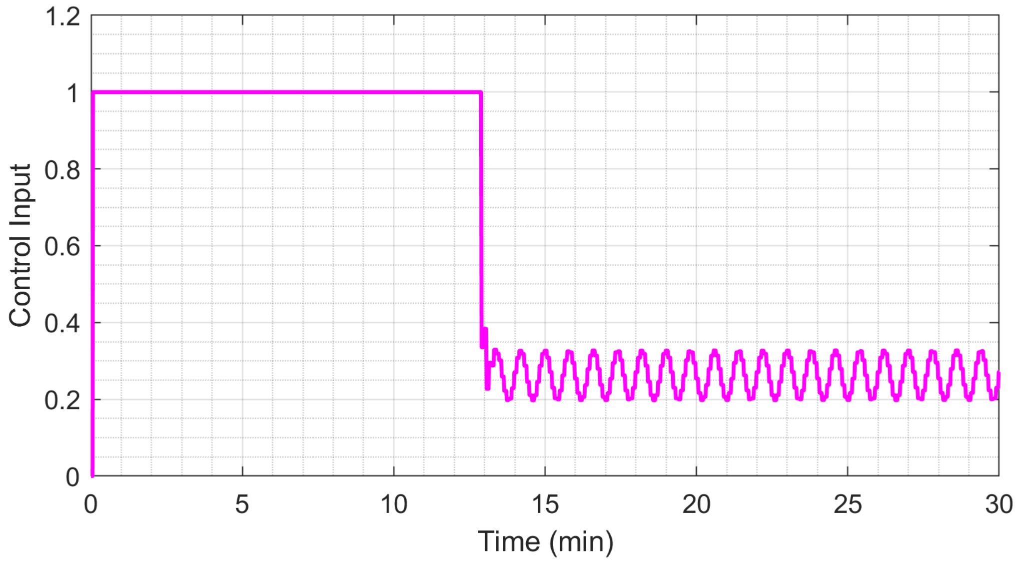
Prediction Horizon	10 sec
Control Horizon	3 sec
Input Constraint	$0 \leq u(t) \leq 1$

4.4. Summary of the Chapter

In this chapter, the design procedure and applications of MPC have been introduced. First, the fundamentals of MPC have been presented. Then, the design procedure of MPC has been described in detail. Lastly, the simulation results of MPC have been presented, demonstrating successful control. It has been stated that due to the constraints and challenges in the implementation, MPC will not be applied in the field.

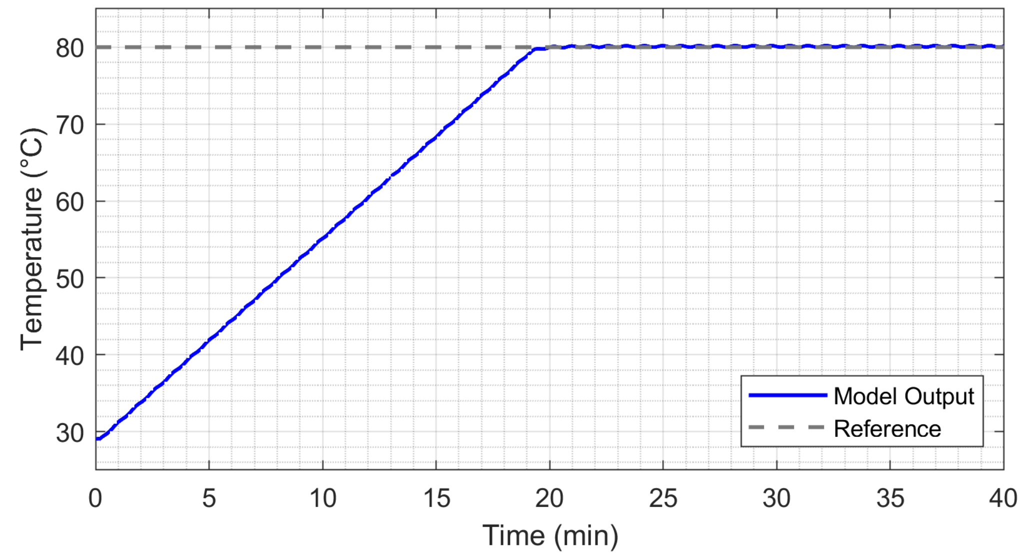


(a)

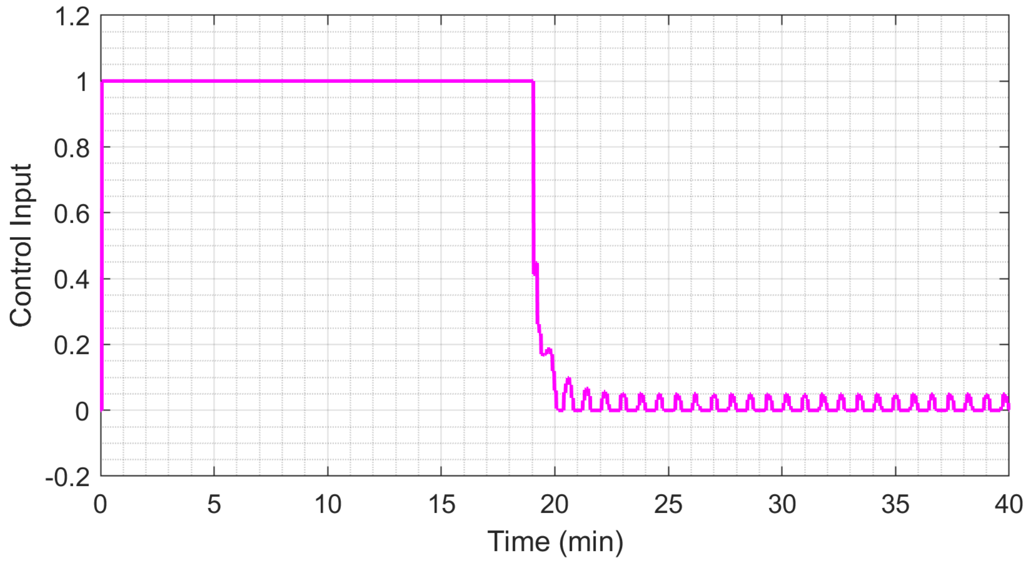


(b)

Figure 4.2. MPC simulation applications for dyeing process | Machine 1 (a) Model output (b) Control input.



(a)



(b)

Figure 4.3. MPC simulation applications for dyeing process | Machine 2 (a) Model output (b) Control input.

5. MODEL-FREE CONTROL ALGORITHMS

Control algorithms that do not utilise a process model while calculating the control input are called model-free control algorithms. In this chapter, two model-free control algorithms, which are adaptive PI control and Error Predictive Control (EPC), will be introduced. First of all, the details of the adaptive PI control are explained by introducing PI tuning methods, which can be found in the literature and are developed in the scope of this thesis. Then, their application results are presented. Lastly, the development procedure of EPC is explained, with its application results provided as well.

5.1. Adaptive PI Control

The adaptive PI control approach is based on tuning the P (Proportional Gain) and I (Integral Time) parameters of the currently used PI controllers in an adaptive manner both offline and in real time. During the offline tuning, the past data are used and the determined controller parameters are constant throughout the process. On the other hand, in real time tuning, the parameters are being tuned while the process continues, by using real time process data. While implementing both these approaches, not only the tuning methods that can be found in literature, but also the tuning methods which are used in industrial applications and designed specifically for the corresponding textile processes will be used. All of the developed algorithms will be verified in the simulation environment first. Later on, the algorithms will be applied to the real processes and the results will be analysed.

5.1.1. PI/PID Tuning In The Literature

There are many PID tuning methods in the literature. O'Dwyer listed 1731 PI or PID controller tuning methods in his book. 60% of these methods are designed for self-regulating processes, 30% are designed for the processes that are not self-regulating and the remaining 10% of these methods are designed for the processes which do not have a certain process model [34]. The reason why there are so many controller tuning methods is because of the fact that processes can be differentiated from each other easily. Since there are a lot of factors affecting a process and almost all of them affect process characteristics, processes can easily be differentiated from each other. As a result of this phenomenon, the development of process-specific controller tuning methods is needed.

One of the main PID tuning methods, which works also as a base for other methods, is developed by Ziegler-Nichols [35]. This method uses the open-loop step input response of the corresponding process and tunes the controller parameters for both scenarios in which PI and PID controllers are used. An open-loop step input response of a first order model can be seen in Figure 5.1.

This step input response, in which K, θ and τ_1 represent the static gain, the dead time and the time constant, respectively, offers the process characteristics as well.

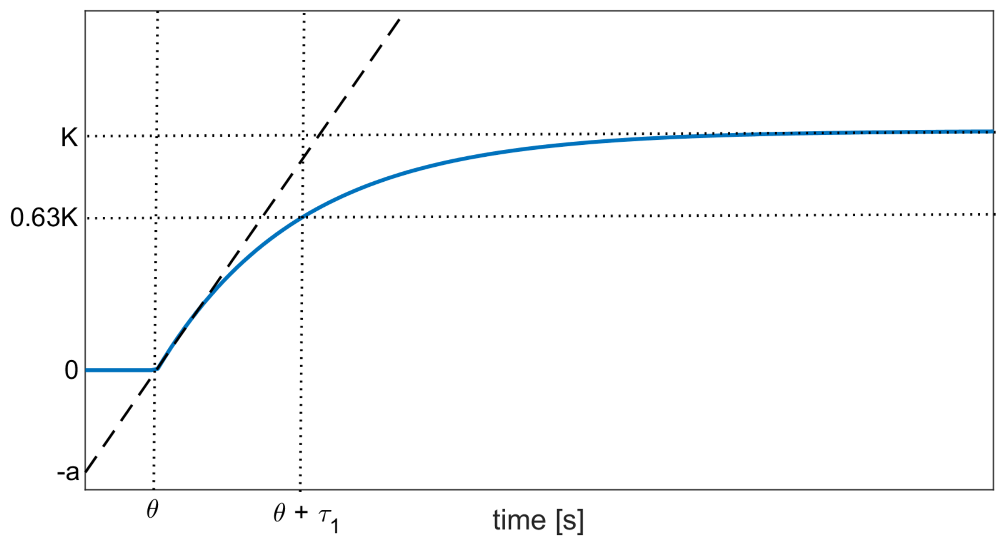


Figure 5.1. Step input response of a first order model [36].

In Table 5.1, the equations that are used to calculate controller parameters for different controller types are displayed.

Table 5.1. Determination of the controller parameters [36].

Controller	$\boldsymbol{K_p}$	$\boldsymbol{T_i}$	$\boldsymbol{T_D}$
P	$1/a$	-	-
PI	$0.9/a$	3.33θ	-
PID	$1.2/a$	2θ	0.5θ

In some cases, calculated parameters do not give sufficient controller performances and further tuning is needed. However, they can still be used as an initial controller parameter set for a newly set up system.

Another PI tuning method in the literature is the relay based method that is proposed by Åstrøm-Hägglund [18], [37]. This method can be viewed as a practical application of the ultimate gain method, which is proposed by Ziegler-Nichols, and it can be considered for industrial applications. The method is mainly based on a relay (ON/OFF) controller. Due to the nature of the relay control, oscillations are obtained automatically. PI controller parameters are tuned by using the amplitude and period values of these oscillations.

There are two relay parameters: the one with high value and the other with low value. These parameters are shown as U_{high} and U_{low} and used to the calculate controller amplitude as

$$G = \frac{U_{high} - U_{low}}{2}. \tag{5.1}$$

In systems that are authorized to have high amplitude oscillations, relay controller parameters can be adjusted as a percentage shown below

$$U_{high} = U_{max} = \%100, \tag{5.2a}$$

$$U_{low} = U_{min} = \%0. \tag{5.2b}$$

In the systems which do not have a relay controller, in order to turn the PI controller into a relay controller, the PI controller parameters can be adjusted as

$$K_p = \text{very high};\ T_i = \text{very high}. \tag{5.3}$$

After adjusting the corresponding controller parameters and getting oscillations, ultimate gain is calculated by using the equations that is given as

$$K_{pn} = \frac{\text{relay output amplitude}}{\text{relay input amplitude}} = \frac{G_u}{G_h} \approx \frac{\frac{4G}{\pi}}{H} = \frac{4G}{\pi H}, \tag{5.4}$$

where $G_h = H$ represents the amplitude of control error signal, $G_u = 4G/\pi$ represents the amplitude of the first harmonic of the Fourier series expansion of the square pulses of the relay controller. By using this ultimate gain value and ultimate period value (T_{in}) which is the oscillation period, the PI parameters are tuned as

$$K_p = 0.45K_{pn}, \tag{5.5a}$$

$$T_i = \frac{T_{in}}{1.2}. \tag{5.5b}$$

5.1.2. Unsuitability of Popular PI/PID Tuning Methods

As discussed above, several PI/PID tuning methods are created either generically or specifically for certain process types. In this section, some popular PI tuning methods will be reviewed and their unsuitability for temperature control in the corresponding textile processes will be discussed [38]. First, open-loop response based methods will be discussed. Then, methods which are established on closed-loop oscillating behaviour will be examined.

5.1.2.1. Open-Loop Response Methods. An open-loop response is the output of a process to a certain input like step or ramp input, without applying any control based on a feedback mechanism which uses process output. Generally, for an open-loop response, the maximum value of the input is applied as step input and enough time is allowed for the process output to settle on a value. By taking this response as a reference, process output is usually fitted to a process model like the first order plus dead-time (FOPTD) and model parameters such as gain, time constant and dead time are calculated. Finally, via these model parameters, PI/PID parameters are tuned.

The aforementioned Ziegler-Nichols' method utilises an open-loop response and uses the corresponding output data to tune the controller parameters of either P, PI or PID controller. Another important open-loop response based PI/PID tuning method is proposed by Skogestad [13]. It is a model-based method in which controller parameters are expressed as functions of the model parameters, which are obtained by fitting open-loop response process output data to the proposed model.

In textile drying and dyeing processes, it is not possible to obtain an open-loop response for the temperature control. As mentioned above, the temperature of the air inside the drum and the temperature of the dye liquid inside the tank are controlled throughout drying and dyeing processes, respectively. The control is carried out by an exchanger mechanism that uses superheated steam able to reach up to 250 °C. But at the same time, the temperature is allowed to reach a maximum of 130 °C due to process and machinery restrictions. This means that it is not possible to apply a fully open steam valve to the system and wait for an adequate time to acquire a steady-state open-loop response temperature value. As a result of this phenomenon, open-loop response based PI/PID tuning methods are not suitable for the corresponding textile processes.

5.1.2.2. Closed-Loop Response Methods. In closed-loop response based PI/PID tuning methods, prespecified controller algorithms are implemented onto the corresponding process with a feedback mechanism. The output of the closed-loop response is used to tune the controller parameters depending on the process and proposed tuning approach. Ziegler-Nichols also proposed a PI/PID tuning method based on the closed-loop response [35]. In this method, a P controller is introduced to the system with a certain P value that causes sustained oscillations. This P value is used with the period value of the oscillations to tune the controller parameters.

Åstrøm-Hägglund's previously mentioned relay-based method can be regarded as a practical implementation of Ziegler-Nichols' closed-loop approach and it utilises a relay (on/off) controller to get sustained oscillations. An ultimate gain value is calculated depending on the input/output gain and this value is used with the oscillation period in the equations, which are proposed in Ziegler-Nichols' method.

The problem with using closed-loop response based PI/PID tuning methods, which require sustained oscillations, is that the process dynamics do not allow to obtain a sustained oscillation behaviour in textile dyeing processes. Even though a P controller with a high P value or a relay controller is used, a proper sustained oscillation behaviour cannot be observed. In Figure 5.2, a closed-response of a dyeing process is shown, which has 80 °C as the reference temperature value and which utilises a P controller with $K_p = 999$ (very high) value, practically behaving like a relay controller. It can be seen that there is no proper sustained oscillation behaviour that can be used to tune PI/PID controller parameters based on the proposed closed-loop response methods.

Therefore, it can be asserted that closed-loop response methods, which are based on oscillating behaviour, are also not suitable for the corresponding textile processes, and developing tuning methods which are specifically designed for them is imperative.

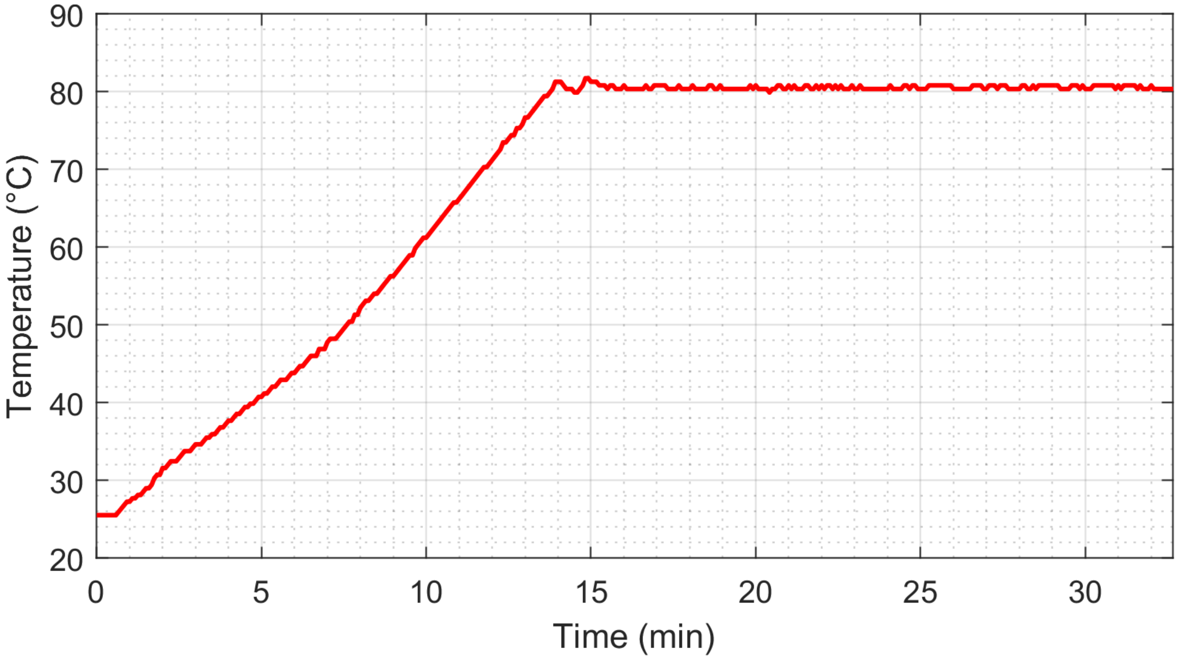


Figure 5.2. Closed-loop response of a textile dyeing process.

5.1.3. Other Tuning Methods

In this work, not only the tuning methods that can be found in the literature but also the tuning methods that are used in the industry and developed exclusively for this work will be utilised. Some of the alternative PI tuning methods which will be considered in this work are as follows:

(i) Adaptive gain method
(ii) Discrete adaptive gain/integral method
(iii) Continuous adaptive gain/integral method

Results of both simulation tests and field applications of these tuning methods will be compared afterwards.

Adaptive Gain Method: This method is based on adaptively changing the default gain parameter of the PI controller, which is procured by field experience over time. The gain parameter is altered in real-time throughout the process depending on the rule-based adaptation mechanism. The mechanism ensures that the PI controller adapts to changing process dynamics faster than a conventional PI controller. The pseudocode of the corresponding adaptation algorithm is given in Figure 5.3.

In this algorithm, ΔT_1 and ΔT_2 represent adaptation band, K_{adap} represents the default adaptation coefficient, K_p represents the default gain parameter, $\overline{K}_{adap}$ represent the current adaptation coefficient and $\overline{K}_p$ represents the current gain parameter. After analysing real process outputs and currently used default PI controller parameters for both drying and dyeing processes, parameters of the adaptive gain algorithm are determined which are given in Table 5.2.

if SP - PV $> \Delta T_1$ **then**
  $\overline{K}_{adap} = 1$
else if SP - PV $> \Delta T_2$ **then**
  $\overline{K}_{adap} = \overline{K}_{adap}$
else
  $\overline{K}_{adap} = K_{adap}$
end if
$\overline{K}_p = K_p \overline{K}_{adap}$

Figure 5.3. Adaptive gain algorithm.

Table 5.2. Parameters of adaptive gain algorithm.

Parameter	**Drying**	**Dyeing**
ΔT_1	2	1
ΔT_2	0.1	0.1
K_p	15	50
K_{adap}	0.66	0.8
T_i	4000	600

Discrete Adaptive Gain/Integral Method: This method is based on adapting both gain and integral parameters of the PI controller to reference the temperature of the corresponding process. Reference temperature groups, as well as gain and integral parameters pertaining to these groups, are determined by reviewing past real process output data from various machines. Parameter sets for two drying and two dyeing machines are given in Table 5.3 and Table 5.4, respectively.

Table 5.3. Discrete adaptive PI Parameters for two drying machines.

Machine No	**Reference Group**							
	$SP \leq 60$		$70 < SP \leq 80$		$80 < SP \leq 90$		$90 < SP$	
	K_p	T_i	K_p	T_i	K_p	T_i	K_p	T_i
1	9	2400	12	3200	15	4000	18	4800
2	10	2667	12	3200	14	3733	16	4267

Table 5.4. Discrete adaptive PI parameters for two dyeing machines.

Machine No	Reference Group							
	$SP \leq 75$		$75 < SP \leq 87$		$87 < SP \leq 108$		$108 < SP$	
	K_p	T_i	K_p	T_i	K_p	T_i	K_p	T_i
1	36	420	40	450	48	550	70	750
2	20	300	30	400	45	500	53	600

Continuous Adaptive Gain/Integral Method: This method is based on adapting both gain and integral parameters of the PI controller depending on the reference temperature of the corresponding process. In this method, gain and integral parameters of a process with a specific reference temperature are determined by applying pseudo open-loop control (applying fully open valves until the maximum temperature limit of the machine is reached) to the corresponding machine and using output data of that process in

$$K_p = c_1 \frac{\tau}{SP - T_0}, \tag{5.6a}$$

$$T_i = c_2 K_p, \tag{5.6b}$$

where SP represents reference temperature, T_0 represents initial temperature, τ represents the time constant of the process (the time it takes for the temperature to reach from T_0 to $T_0 + 0.632(SP - T_0)$), c_1 and c_2 represent tuning coefficients. c_1 and c_2 are chosen as 0.25, 267 and 3.3, 12 for drying and dyeing processes, respectively. Obtained tuning curves for corresponding drying and dyeing machines are given in Figure 5.4 and Figure 5.5, respectively.

5.1.4. PI Control Applications

In this section, applications of proposed tuning methods will be presented for both drying and dyeing processes. First off, applications in the simulation environment will

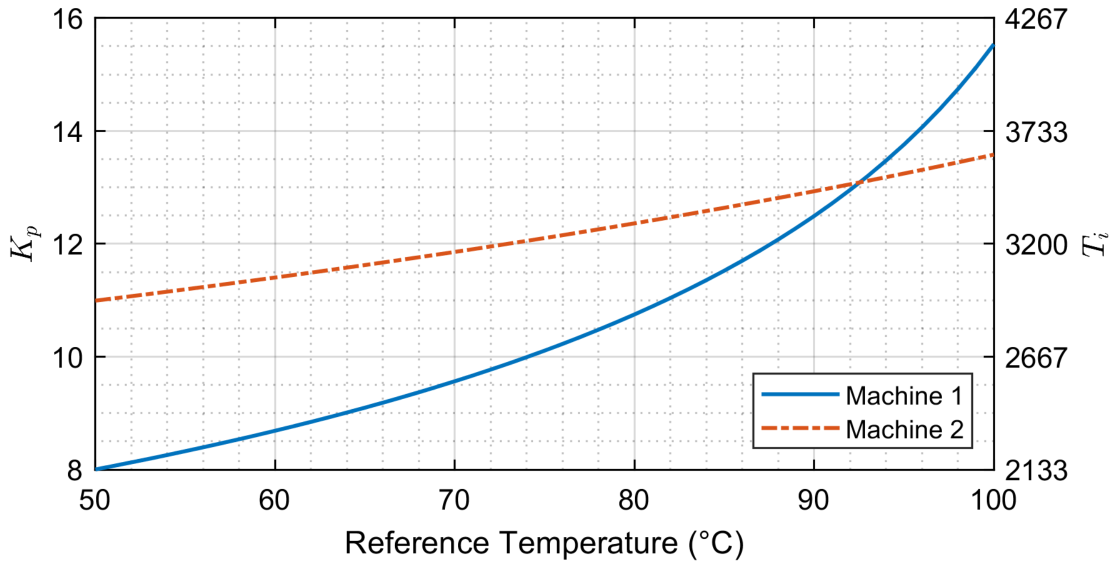


Figure 5.4. Continuous adaptive gain/integral method tuning curves for two drying machines.

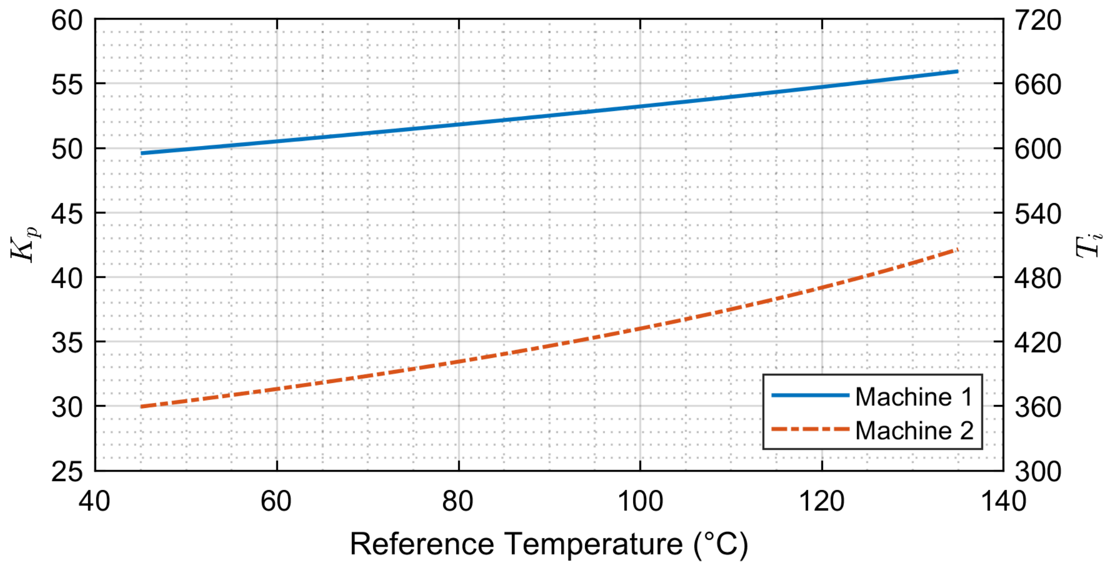


Figure 5.5. Continuous adaptive gain/integral method tuning curves for two dyeing machines.

be introduced. After that, the selected tuning methods with satisfactory results in simulations will be implemented on the actual machines in the field.

5.1.4.1. PI Control Simulation Applications. A simulation environment is created by using MATLAB, which utilises constructed process models. To be able to make the simulation environment as similar as possible to the field environment, the aforementioned process dynamics such as sensor resolution and noise are also incorporated into it.

For drying applications, the model parameters that are given in Figure 3.2 and Figure 3.3 for Machine 1 and Machine 2, respectively, are used. Application results from the simulation are displayed in Figure 5.6 and Figure 5.7.

It can be noted that the proposed methods yield better results in both application outcomes, compared to the conventional control. The conventional control witnesses oscillations and higher steady-state error against the controls whose parameters are tuned by the proposed methods, which give more or less matching results between each other. That being the case, it is better to use the easier to implement adaptive P method in the field applications.

For dyeing applications, the model parameters that are given in Figure 3.4 and Figure 3.5 for Machine 1 and Machine 2, respectively, are deployed. Simulation application results are shown in Figure 5.8 and Figure 5.9.

Dyeing simulation application results show that the proposed tuning methods give similar or slightly better control performance compared to the conventional methods. This outcome is particularly important because, while the control performance stays similar, which is already good, it reduces the setup time of the machine which relies on field experts for controller tunings. As a result, discrete adaptive PI is chosen to be applied for real processes.

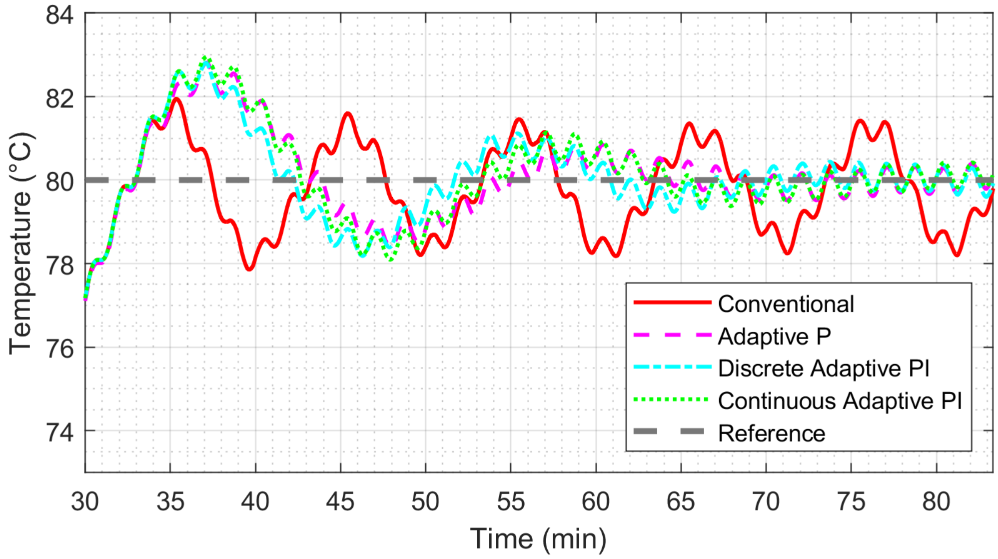


Figure 5.6. PI control simulation applications for drying process | Machine 1.

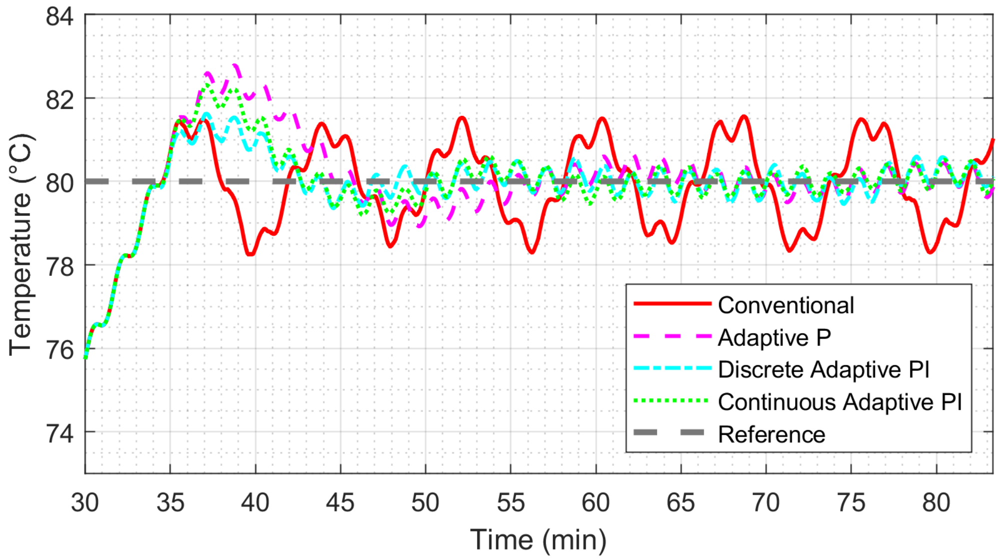


Figure 5.7. PI control simulation applications for drying process | Machine 2.

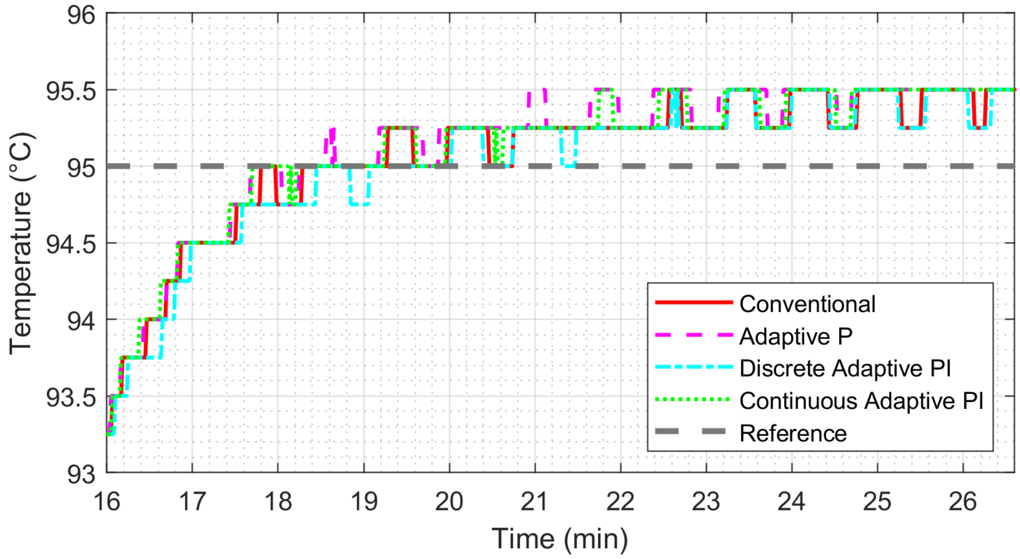


Figure 5.8. PI control simulation applications for dyeing process | Machine 1.

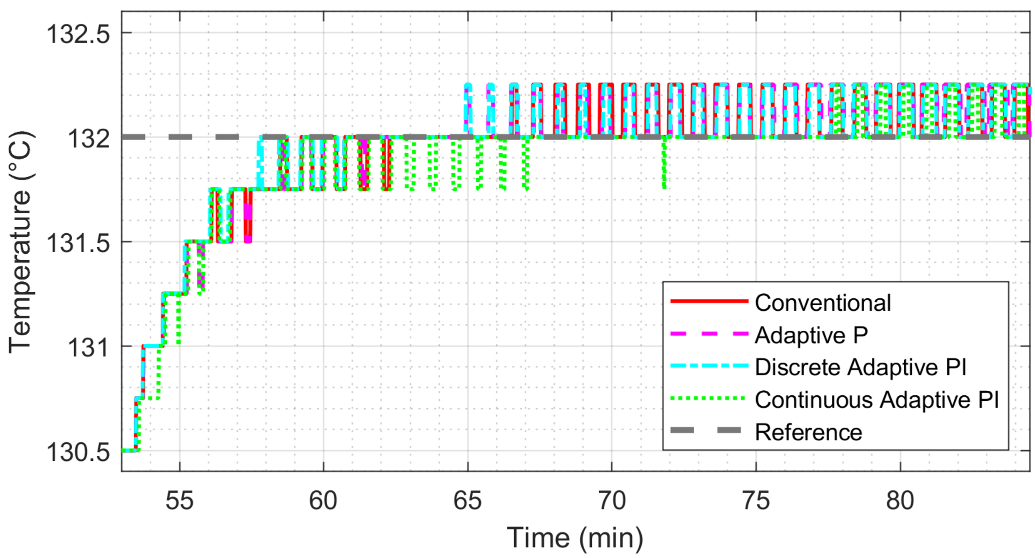


Figure 5.9. PI control simulation applications for dyeing process | Machine 2.

5.1.4.2. PI Control Field Applications. To be able to apply the proposed tuning methods in the field to real processes, they must first be implemented using the appropriate software, which is C, so that process control devices can utilise them. Adaptive P and discrete adaptive PI methods are implemented for drying and dyeing processes, respectively. Several drying and dyeing machines are selected from pilot dyehouses and controller applications are executed with the guidance of corresponding engineers and field experts. Then, a certain amount of time (a couple of weeks) is required to have a sufficient number of processes. At last, output data of these processes are collected and analysed to determine the performance results of the proposed tuning methods.

Three machines are selected for drying field applications, the first two of which are previously modelled ones. In Figure 5.10 and Figure 5.11, the field application examples for Machine 1 and Machine 2 are respectively shown. The complete field application control performance results are shared in Table 5.5.

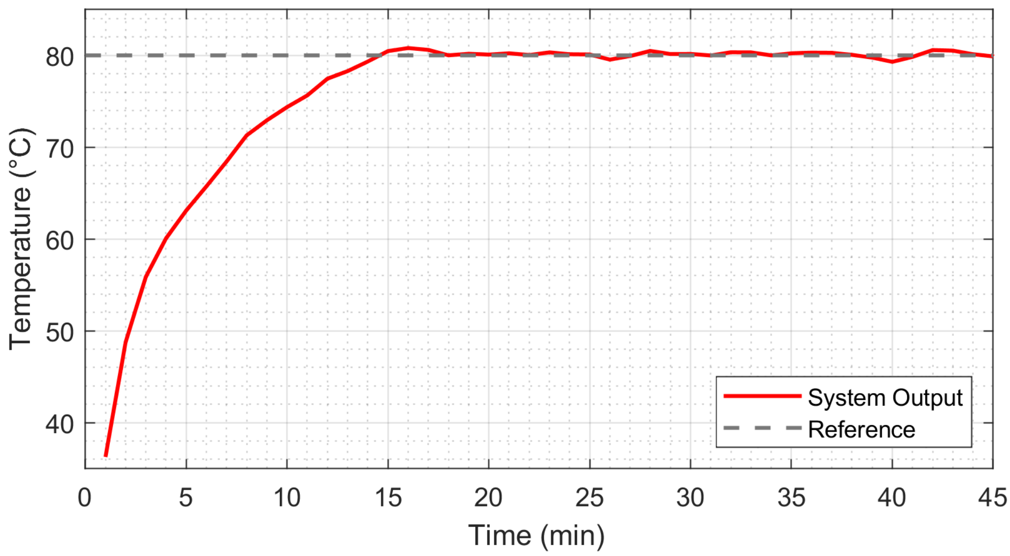


Figure 5.10. PI control field applications for drying process | Machine 1.

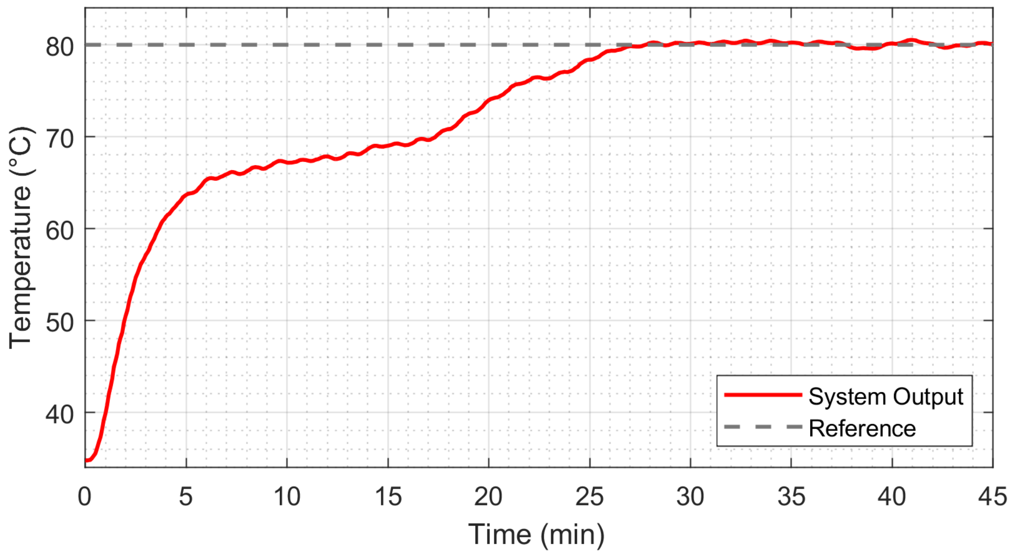


Figure 5.11. PI control field applications for drying process | Machine 2.

Table 5.5. PI control field applications controller performance assessments for drying process | Number: Number of controlled processes.

Machine No	**Conventional**			**Adaptive P**		
	Number	OV	SSE	Number	OV	SSE
1	493	-2.44	3.42	1350	1.12	0.86
2	1040	-1.93	3.40	641	1.77	0.87
3	856	-1.71	3.53	1411	2.02	0.87

It can be deduced that the PI controller, which is tuned by the adaptive P method, displays better control performances compared to the PI controller which is conventionally tuned for drying processes.

In Figure 5.10 and Figure 5.11, references are tracked very successfully without any major overshoots and oscillations. At the same time, since steady-state errors are almost zero, it can be claimed that control performances are almost perfect. Table 5.5 also declares important results: for example, for each different machine, a conventional PI controller has negative overshoot values meaning undershoots, with considerably high steady-state errors. It indicates that the reference temperatures cannot even be attained with a conventional PI controller, which is not an acceptable control performance. On the contrary, with the PI controller tuned by the adaptive P method, processes have only a small amount of overshoots, and steady-state errors of less than 1 °C, which are both successful control performances. Because the number of the controlled processes is almost 5000, it can also be said that these results cover all of the differences in the processes and the comparison between the controllers is fair. By taking into consideration all of these results, it can be concluded that the developed adaptive P method is a successful tuning method and can be used for tuning PI controllers for drying processes.

For dyeing field applications, 6 machines are selected, the first two of which are previously modelled ones. In Figure 5.12 and Figure 5.13, the field application examples for Machine 1 and Machine 2 are shown, respectively. The complete field application control performance results are given in Table 5.6, in which some of the previously mentioned statistical metrics and performance indices are used for controller performance assessments.

It can be inferred that the PI controller tuned by the discrete adaptive PI method gives better control performances compared to the PI controller which is tuned conventionally for dyeing processes. In Figure 5.12 and Figure 5.13, it can be observed that there are successful reference trackings with acceptable overshoots and nearly zero steady-state errors. Table 5.6 ensures a comprehensive comparison because it covers even more metrics. Two controllers that controlled up to 10000 processes for 6 different machines are compared.

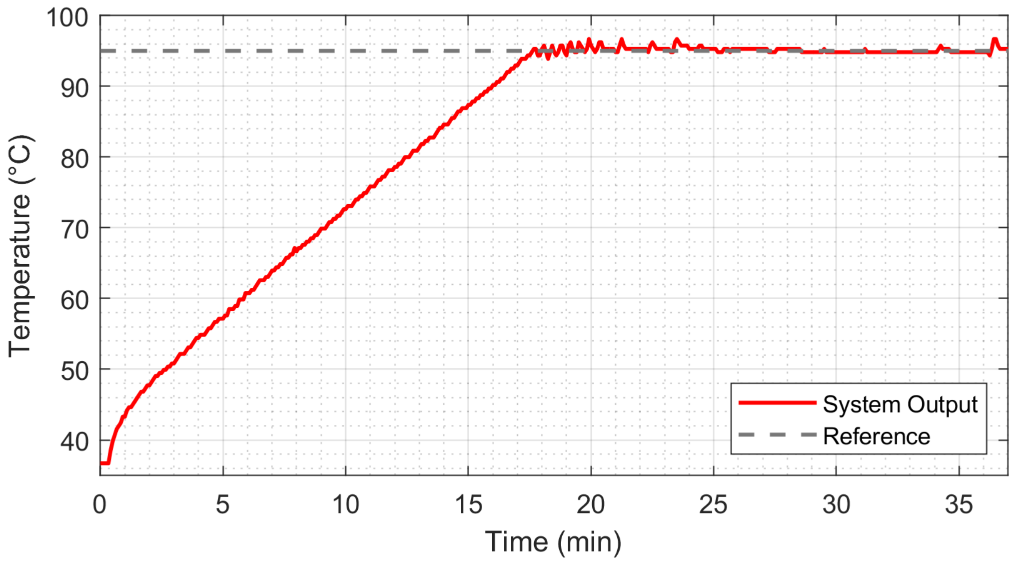


Figure 5.12. PI control field applications for dyeing process | Machine 1.

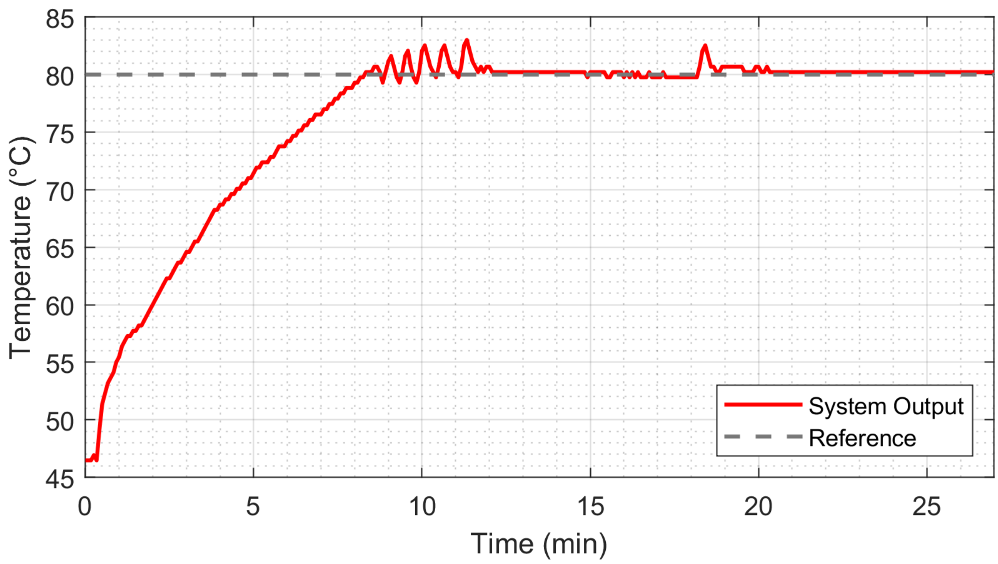


Figure 5.13. PI control field applications for dyeing process | Machine 2.

For most of the metrics, the PI controller that is tuned by the proposed method has better results compared to the conventional PI controller. For example, all of the performance success values are higher in the proposed method. MAE, which is another example, is also in favour of the proposed method for 4 machines. In the end, for an overall comparison, it can be concluded that the developed discrete adaptive PI method is a successful tuning method and can be used for tuning PI controllers for dyeing processes.

Table 5.6. PI control field applications controller performance assessments for dyeing process | Number: Number of controlled processes.

Machine No	**Number**	**Statistical Metrics**					**Harris Index**	**Performance Success**
		Var.	St. Dev.	MAE	MSE	RMSE		
1	822	0.14	0.34	0.45	0.34	0.55	0.50	88.38
2	1157	0.23	0.43	0.51	0.48	0.68	0.42	75.49
3	843	0.26	0.46	0.51	0.52	0.69	0.49	73.33
4	710	0.15	0.35	0.48	0.42	0.61	0.41	84.2
5	844	0.06	0.23	0.33	0.18	0.38	0.48	97.43
6	538	0.27	0.46	0.62	0.61	0.76	0.40	68.69

(a) Conventional PI

Machine No	**Number**	**Statistical Metrics**					**Harris Index**	**Performance Success**
		Var.	St. Dev.	MAE	MSE	RMSE		
1	492	0.14	0.35	0.43	0.32	0.54	0.52	88.48
2	476	0.22	0.41	0.53	0.50	0.67	0.40	76.73
3	611	0.20	0.41	0.42	0.37	0.58	0.49	80.61
4	610	0.13	0.32	0.43	0.36	0.56	0.45	87.58
5	783	0.07	0.24	0.34	0.20	0.41	0.44	97.54
6	670	0.26	0.48	0.49	0.47	0.65	0.50	72.01

(b) Discrete Adaptive PI

5.2. Error Predictive Control

The other method that is developed by using the model-free control approach is the Error Predictive Control (EPC). The control input is determined by the predictions in the reference tracking error, which are based on the internal dynamics of the associated process itself. Firstly, a newly developed model-free controller that is called Rate Predictive Control (RPC) will be introduced. Following that, EPC, which is based on RPC but with several fundamental differences, will be presented. In the end, the simulation and real process application results of using these controllers will be given with the performance analyses.

5.2.1. Rate Predictive Control

RPC [39] was the starting point for the development of model-less control algorithms. In this control approach, the predicted system output is used as feedback instead of the real system output. Additionally, the controller output is calculated in an integrative manner. In this section, firstly, the design of RPC will be introduced. Later, simulation and field application results of RPC will be given.

5.2.1.1. RPC Design. RPC control approach has two main parts, which are the prediction part and the control move calculating part. In the prediction part, a system output is predicted by using the real system output; while in the control move calculating part, the error, which is calculated as the difference between the real system output and the predicted output, is utilised in certain mathematical equations and a control move is calculated accordingly. This control move is added to the latest controller output and thus a new controller output is measured. The control scheme of RPC is given in Figure 5.14.

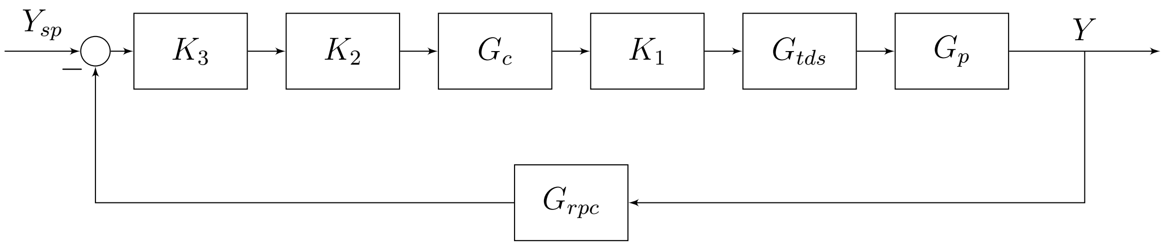


Figure 5.14. Control scheme of RPC [39].

In this scheme, K_1 represents the process gain, K_2 represents the maximum rate of change of the corresponding control variable, K_3 represents the sensitivity band, Y represents the control variable, Y_{sp} represents the set point of the control variable, G_c represents the controller transfer function, G_{tds} represents the transfer function of the time delay, G_p represents the process transfer function and G_{rpc} represents the transfer function of the rate prediction. The transfer functions that will be used in the simulations are given as

$$G_c = \frac{1}{s}, \tag{5.7a}$$

$$G_{tds} = e^{-t_d s}, \tag{5.7b}$$

$$G_{rpc} = \theta s + 1, \tag{5.7c}$$

where t_d represents the time delay of the system and θ represents the prediction rate. For G_p and K_1, previously developed transfer functions and mathematical models will be used.

The other approach that is proposed in RPC is the smart dead band approach. Contrary to the conventional dead band approach, calculated controller moves are adjusted according to the error and as the error goes to zero, the controller moves go to zero as well. The mathematical equation of the proposed approach is given in [40] as

$$\text{smart move} = min(abs(e)K_3^{-1}K_2, K_2). \tag{5.8}$$

In this algorithm, e represents the error as the difference between the reference value and the system output value. Control algorithms which are designed using this approach will be simulated with the developed system models and they will be applied to the real processes.

5.2.1.2. RPC Applications. To be able to apply RPC in the simulation environment and the field, RPC algorithms are implemented in the corresponding software, similar to PI control applications. Following its implementation, RPC is simulated for a dyeing process using the model shown in Figure 3.4. The simulation output is shown in Figure 5.15 in which RPC parameters are chosen as $K_2 = 20$, $K_3 = 1.25$ °C, $\theta = 2$ (K_1 and t_d are placed inside of the model). The simulation result shows a decent control performance.

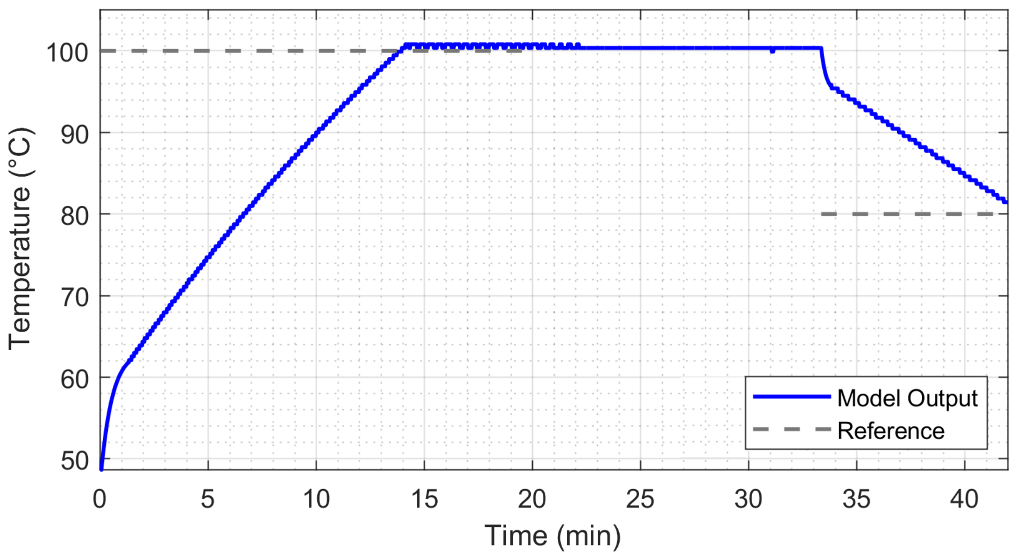


Figure 5.15. RPC simulation application for dyeing process.

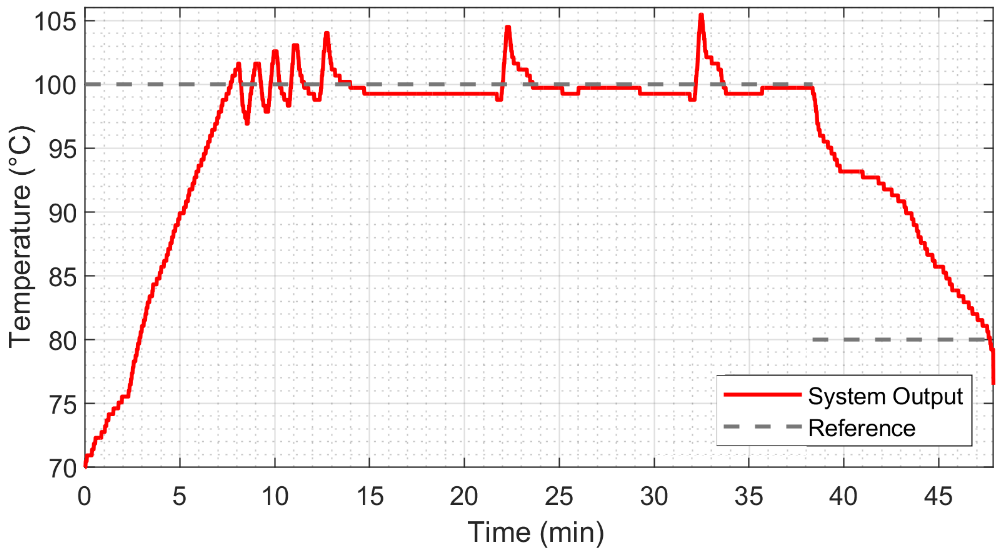


Figure 5.16. RPC field application for dyeing process.

Consequently, RPC is applied to a real dyeing process whose output is given in Figure 5.16, which uses the same parameters as the simulation application.

5.2.2. Error Predictive Control

Examination of the RPC field application results reveal that the performance of RPC is not satisfactory. As a result, it is necessary to enhance the RPC algorithms to attain better controller performance. Understanding what causes the undesirable behaviour is vital for developing new algorithms. After studying the prediction algorithms of RPC, it is understood that the prediction algorithm was basically a derivative operator.

Due to the nature of the derivative operator, it is beneficial to have a continuous variable to apply the derivative. However, in the real textile processes that are being worked on, the control variables have a discrete measurement structure which makes them unsuitable for the derivative operator. It leads to poor derivative operations which eventually result in poor predictions.

The other handicap of the prediction algorithms of RPC is the lack of a sufficiently long prediction horizon. In the prediction algorithms of RPC, in each control cycle, the prediction is made for the very next control cycle. So, it means that the prediction horizon equals to the period of the control cycle. For the corresponding textile processes, one second control period is used which is far from being an adequate prediction horizon. Predictions which are relatively shorter than the system delay are practically useless.

Due to the aforementioned issues with RPC algorithms, it is decided that a new control approach is needed to be developed. After some research and analyses, a novel control approach is developed, which is named Error Predictive Control (EPC), and it not only solves the problems of the RPC algorithms but also conserves the model-less control structure. In the continuation of this section, the design of the EPC algorithms and their difference from the RPC algorithms will be introduced. Afterwards, the simulation and field application results will be presented.

5.2.2.1. EPC Design. It is mentioned previously that RPC uses the derivative operator for prediction and this was responsible for problematic predictions. For that reason, it can be claimed that to overcome this issue, prediction algorithms should be designed in a more convenient way for the corresponding textile processes. After doing some analyses on process behaviours, it is concluded that the linear extrapolation method, which does not depend on any model and is easy to apply, can be utilised for prediction. In this method, process outputs are predicted for a certain prediction horizon by using process outputs up to a particular point in the past. For making predictions, the aforementioned least squares technique is employed. The main design parameters of this approach are the prediction past (T_{past}) and the prediction horizon (T_{hor}), which are in seconds. An example of linear extrapolation is given in Figure 5.17.

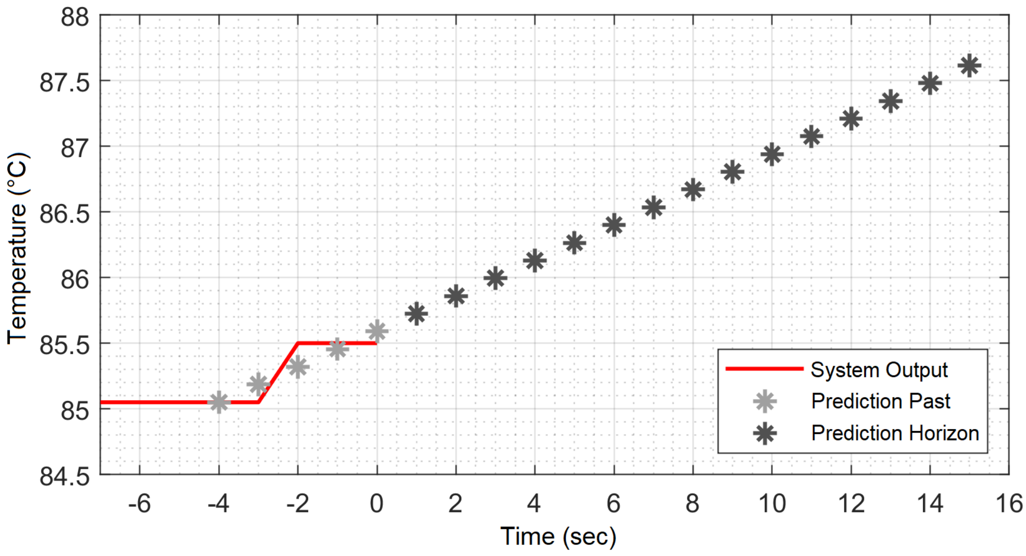
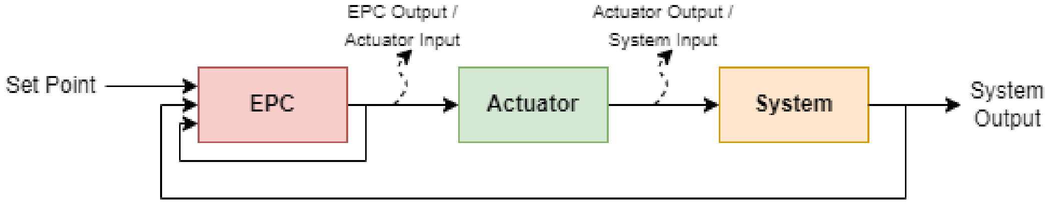


Figure 5.17. An example of EPC linear extrapolation.

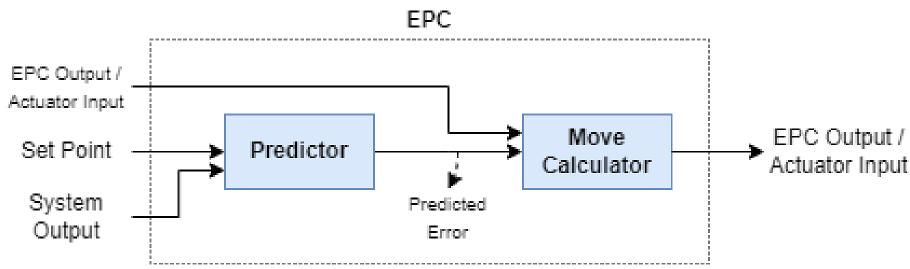
It is also observed that the smart move approach in RPC does not give decent results. In the RPC algorithms, the more it is closer to the reference, the more sensitivity of control moves increases, and when the error becomes zero, control moves are reset. However, due to the measurement resolutions of the corresponding textile processes, it is not possible to have a zero error value. Due to this phenomenon, regardless of how close the process output is to the reference, a non zero control move is calculated in the RPC approach. The problem requires an update in the smart dead band approach of RPC. The algorithms belonging to the new smart dead band approach, which is developed for EPC, can be seen in Figure 5.18 where K_4 represents the dead band parameter. In this approach, control moves are set to zero while the predicted error (e_{pred}) is in dead band which means that the control output of the EPC stays constant. Figure. 5.19 shows EPC control schemes that have been obtained after a period of development. The proposed EPC approach will both be simulated in the simulation environment and applied to the real textile processes as well.

if $abs(e_{pred}) > K_4$ **then**
  smart move $= min(abs(e_{pred}) * K_3^{-1} * K_2, K_2)$
else
  smart move $= 0$
end if

Figure 5.18. EPC smart move algorithm.



(a)



(b)

Figure 5.19. EPC controller schemes (a) Main control scheme (b) Internal EPC scheme.

<u>5.2.2.2. EPC Applications.</u> EPC is also applied both in the simulation environment and in the field similarly to PI control and RPC applications. For simulation applications, the models given in Figure 3.2 and Figure 3.4 are used for drying and dyeing simulations, respectively. For drying simulation applications, EPC parameters as chosen as $K_2 = 5$, $K_3 = 1$ °C, $K_4 = 0.5$ °C, $T_{past} = 5$ sec and $T_{hor} = 10$ sec. For dyeing simulation applications, EPC parameters as chosen as $K_2 = 20$, $K_3 = 1.25$ °C, $K_4 = 0.5$ °C, $T_{past} = 5$ sec and $T_{hor} = 15$ sec. Simulation application results for drying and dyeing processes are shown in Figure 5.20 and Figure 5.21, respectively.

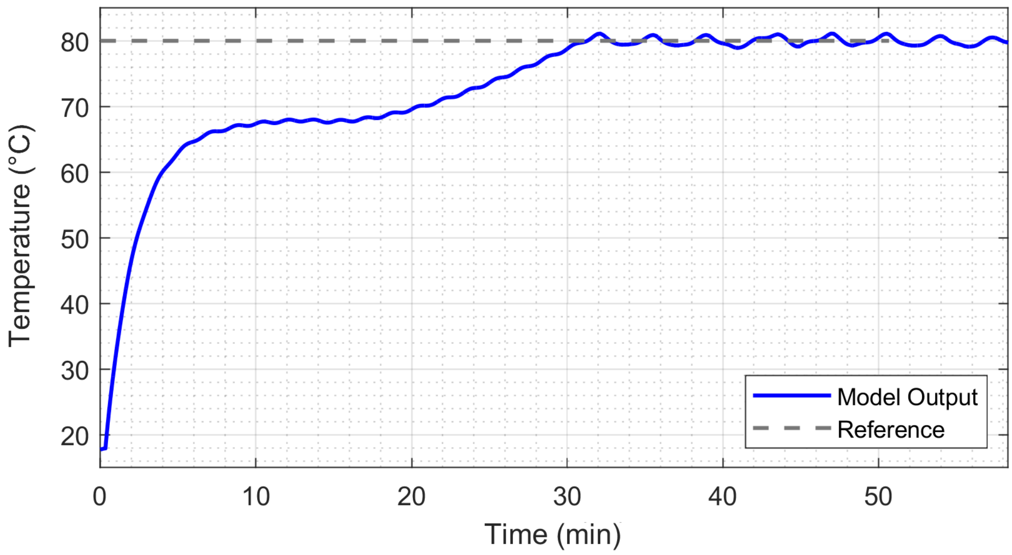


Figure 5.20. EPC simulation application for drying process.

After simulation applications, which have decent control performances, EPC is applied to the real processes in the field. Even though EPC is most suitable to control relatively slow processes due to its characteristics, it is also applied to drying processes, which are processes compared to dyeing processes, so that one can understand its control performance for fast processes. First, pre-application works are done to be able to determine default EPC parameters for drying processes. EPC parameters are tuned in time. One of the first field application results for a drying process is shown in Figure 5.22, in which EPC parameters are chosen as $K_2 = 5$, $K_3 = 2.5$ °C, $K_4 = 1$ °C, $T_{past} = 10$ sec and $T_{hor} = 20$ sec.

Constant oscillations in the system output signify that there is no acceptable control performance. Therefore, to prevent oscillatory control, EPC parameters are tuned where the band parameter is increased and the step parameter is decreased. Field application results with the tuned EPC are shown in Figure 5.23, in which EPC parameters are chosen as $K_2 = 0.25$, $K_3 = 4$ °C, $K_4 = 1$ °C, $T_{past} = 10$ sec and $T_{hor} = 20$ sec.

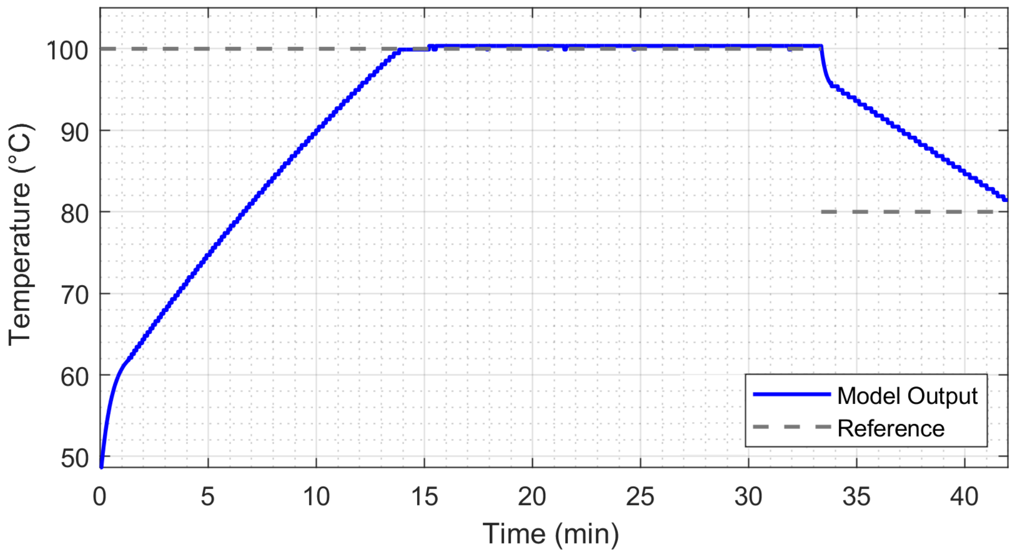


Figure 5.21. EPC simulation application for dyeing process.

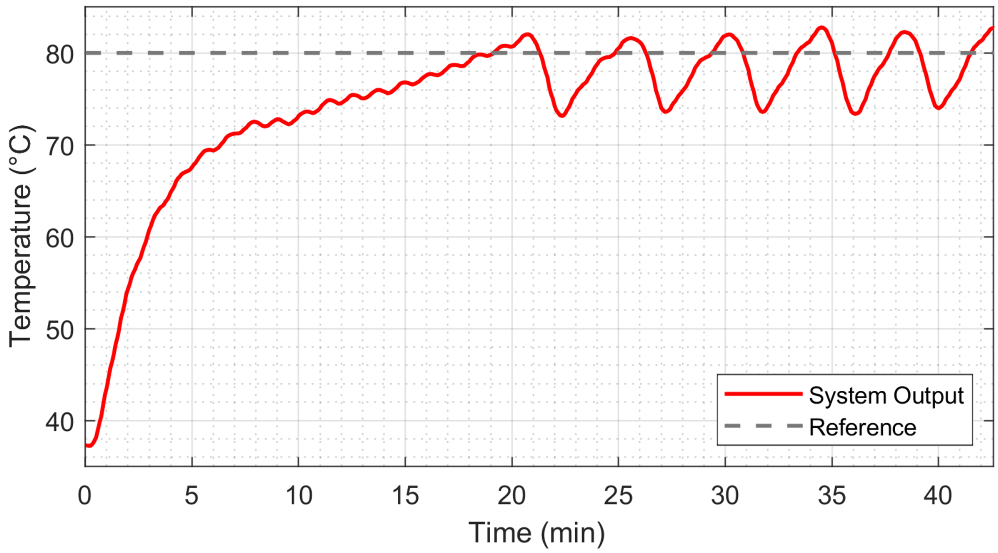


Figure 5.22. EPC field application for drying process | Application 1.

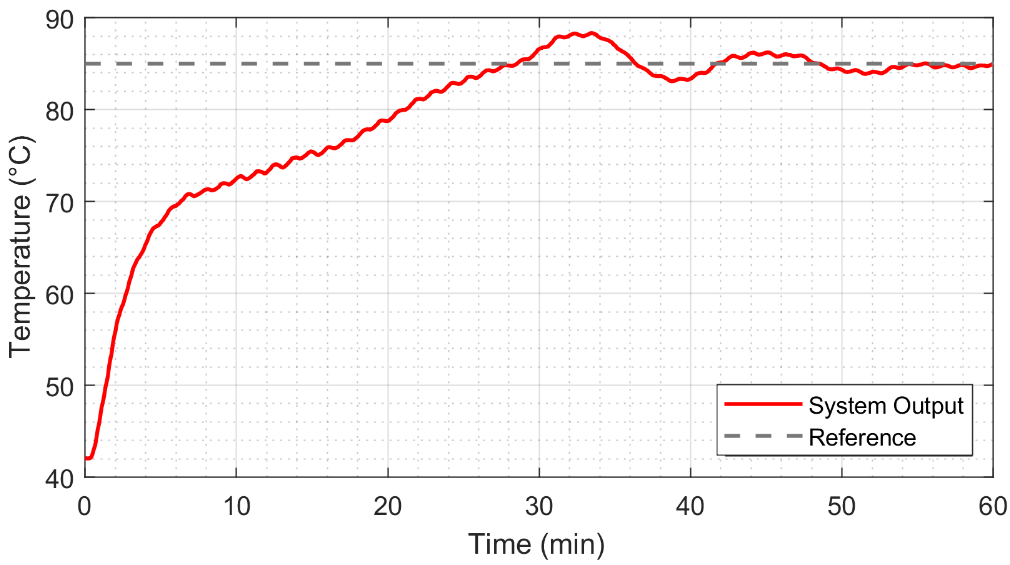


Figure 5.23. EPC field application for drying process | Application 2.

In this application, although the overshoot is slightly increased, the steady-state error is decreased considerably and constant oscillations are prevented completely. Even if EPC gives acceptable control performances for some drying processes, application results for different machines and parameter sets are not acceptable in general because EPC is suitable for slow processes, as mentioned previously. Therefore, EPC field applications for dyeing processes will be given more focus from this point on.

Unlike drying processes, there was not a parameter set of EPC for dyeing processes, since EPC is a completely novel controller. For this reason, various parameter sets are tried and tuned to find the suitable parameter set in the end. EPC has more parameters than the PI controller and EPC's parameters are more inclusive compared to the PI controller. The same EPC parameter set can be used for different machines, while utilising the same PI parameter set for different machines may not yield decent control performances in the long run. This situation is one of the main advantages of EPC. After a sufficient number of field applications, the ultimate EPC parameter set is determined for dyeing processes.

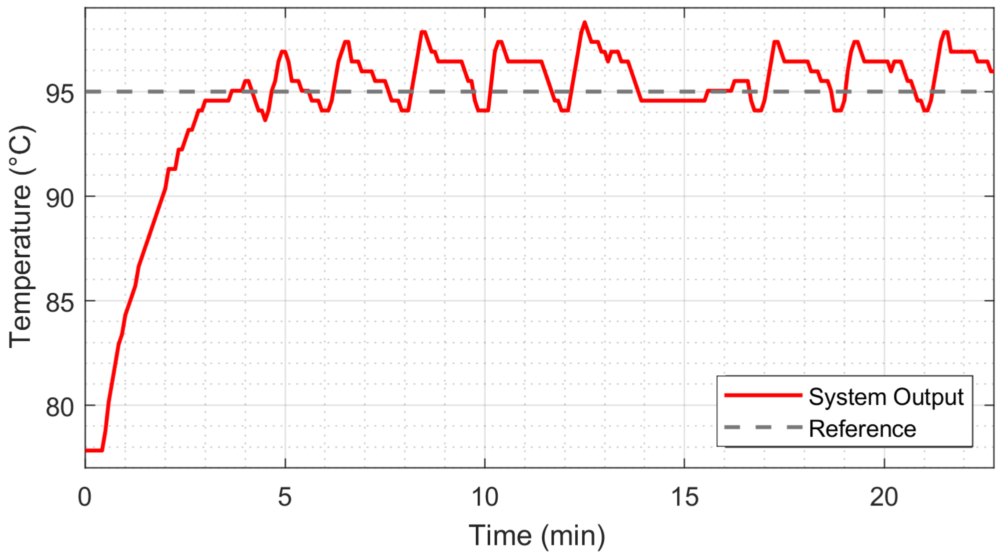


Figure 5.24. EPC field application for dyeing process | Application 1.

One of the first field application results for a dyeing process is shown in Figure 5.24 where EPC parameters are chosen as $K_2 = 20$, $K_3 = 1.25$ °C, $K_4 = 0.5$ °C, $T_{past} = 40$ sec and $T_{hor} = 20$ sec. Even though there is unacceptable control performance due to high overshoot and constant oscillations, it is confirmed that there is no problem with the implementation of EPC to the corresponding software.

Initially, to prevent oscillations, which are caused by fast control output movements, the step parameter is decreased. Prediction past and prediction horizon are also decreased so as to improve the accuracy of predictions around the reference temperature. Additionally, to avoid unnecessary control movements, the dead band parameter is increased. Field application result that utilises the new parameter set is shared in Figure 5.25 where EPC parameters are chosen as $K_2 = 2$, $K_3 = 1.25$ °C, $K_4 = 0.9$ °C, $T_{past} = 40$ sec and $T_{hor} = 15$ sec. Despite the fact that constant oscillations disappear, there are still some issues in the control like initial overshoot and temperature increase in the steady-state. To be able to prevent the initial overshoot, it is essential to have improved predictions, which can be ensured by extending prediction past and horizons.

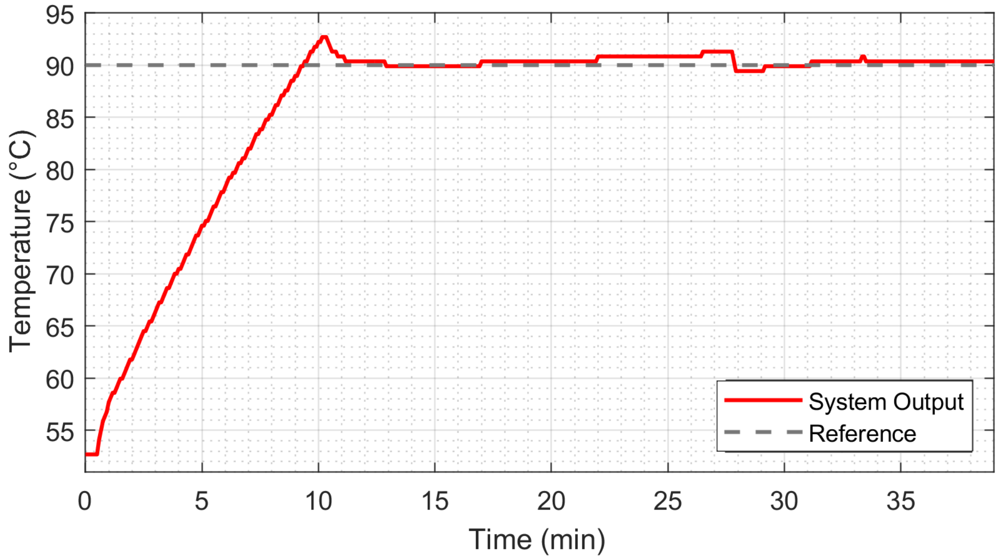


Figure 5.25. EPC field application for dyeing process | Application 2.

On the other hand, usage of constant prediction parameters makes predictions inconsistent because of the dynamic characteristics of dyeing processes. Therefore, different prediction parameters are starting to be used for different regions of the process. Similar to the dyeing modelling, the dyeing process is divided into two regions which are rapid heating and constant temperature. Different prediction parameters are determined based on the dynamics of the corresponding process region. Moreover, band and step parameters are updated. The field application result of these changes is given in Figure 5.26, in which EPC parameters are chosen as $K_2 = 1$, $K_3 = 2.50$ °C, $K_4 = 0.9$ °C, $T_{past} = 30/5$ sec and $T_{hor} = 60/25$ sec. In this process, the second prediction parameter set begins to be used after the 10th minute and a considerable amount of decrease in overshoot is achieved thanks to the better predictions which are made closer to the reference temperature. At the same time, due to the adjustments in band and step parameters, movements in the steady-state are decreased, causing a decrease in steady-state error. Overall, this control performance can be regarded as successful.

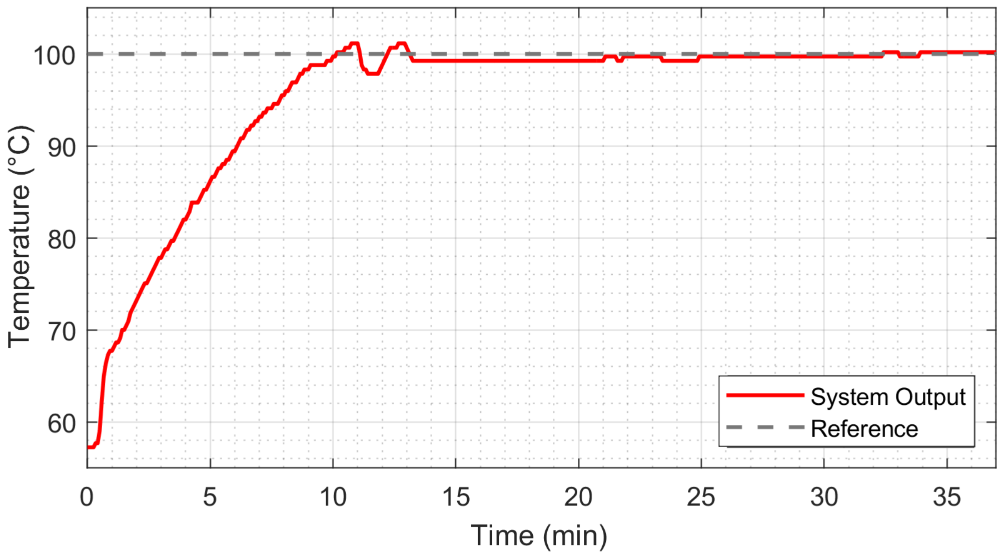


Figure 5.26. EPC field application for dyeing process | Application 3.

Even though successful control is achieved, it is possible to increase control performances even more. As a consequence, field applications are continued to find a new parameter set that gives superior control performances. After increasing the to prevent unnecessary control movements, the ultimate EPC parameter set is obtained whose field application result is given in Figure 5.27 where EPC parameters are chosen as $K_2 = 1$, $K_3 = 2.50$ °C, $K_4 = 1.0$ °C, $T_{past} = 30/5$ sec and $T_{hor} = 60/25$ sec. It can be argued that almost perfect control performance is achieved where overshoot and the steady-state error are nearly zero.

After obtaining the ultimate EPC parameter set, EPC is applied to more than 500 real dyeing processes, using different dyeing machines from PI control applications. The results are displayed in Table 5.7. In this table, in addition to the previously mentioned control performance assessment tools, valve (ON/OFF and proportional) and steam cost metrics, which demonstrate one of EPC's main advantages, are also included. Steam cost is not calculated via direct consumption due to the absence of corresponding data. Instead, the cumulative sum of proportional valve opening values is used.

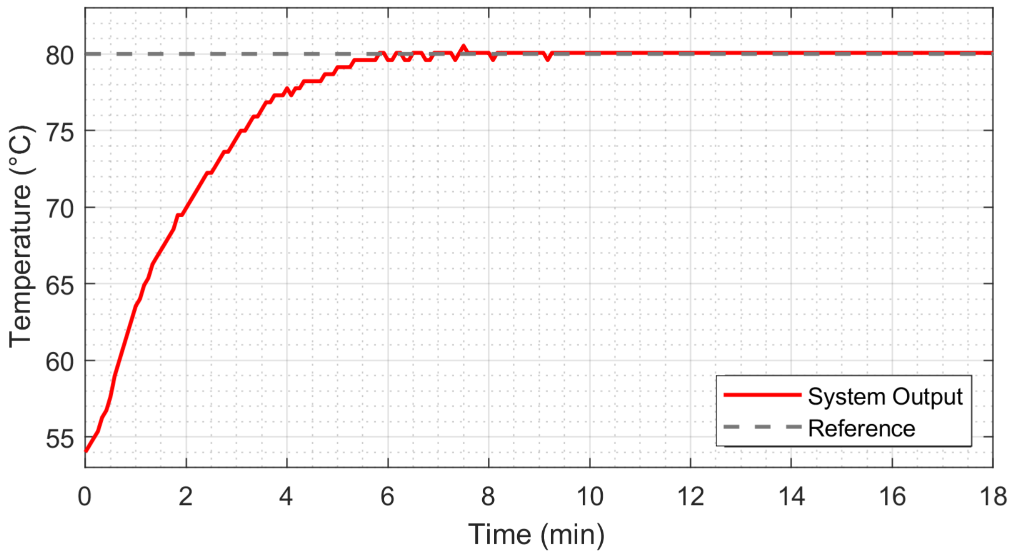


Figure 5.27. EPC field application for dyeing process | Application 4.

It can be claimed that even though EPC gives slightly less successful control performances in general, they are still acceptable control performances with considerable advantages for valve usage and steam consumptions. In consequence, the user can evaluate the trade-off and select the proper controller accordingly.

Table 5.7. EPC field applications controller performance assessments for dyeing process | Number: Number of controlled processes.

Machine No	**Number**	**Statistical Metrics**					**Harris Index**	**Performance Success**	**Costs (Per minute)**		
		Var.	St. Dev.	MAE	MSE	RMSE			ON/OFF	Proportional	Steam
7	1466	0.08	0.26	0.37	0.20	0.40	0.44	94.59	4.01	7.27	35.98
8	1506	0.09	0.27	0.29	0.14	0.35	0.47	93.67	2.78	9.14	37.53
9	1300	0.14	0.34	0.42	0.29	0.52	0.47	88.93	1.62	5.53	25.12

(a) Conventional PI

Machine No	**Number**	**Statistical Metrics**					**Harris Index**	**Performance Success**	**Costs (Per minute)**		
		Var.	St. Dev.	MAE	MSE	RMSE			ON/OFF	Proportional	Steam
7	285	0.13	0.33	0.50	0.35	0.57	0.28	88.13	1.76	1.89	29.71
8	308	0.13	0.34	0.48	0.32	0.54	0.27	90.88	0.80	2.00	36.2
9	286	0.16	0.36	0.67	0.63	0.76	0.21	68.47	1.22	1.51	24.36

(b) EPC

5.3. Summary of the Chapter

In this chapter, model-free control algorithms have been introduced. In the beginning, adaptive PI control has been explained by introducing several PI tuning methods and the application results have been shared, in which the success of developed algorithms over conventional ones has been verified through the aforementioned performance assessment tools. Then, EPC and its development procedure have been explained by simultaneously presenting the application results. It has been confirmed that EPC has compatible control performances compared to conventional control, while also providing considerable cost reductions. In the end, it has been deduced that the PI controllers utilising the developed tuning methods and EPC are superior to the conventional control.

6. CONCLUSION

Temperature control in drying processes and dyeing processes are two main control objectives in the textile industry. Conventionally, the control of temperature is done by PI controllers. The PI controllers are usually tuned by field experts and most of the time setup procedures and controller parameters stay constant throughout the lifetime of the machine. Due to the dynamic nature of drying and dyeing processes, however, the controller parameters require tuning occasionally. Otherwise, the temperature control starts to become unsatisfactory over time and the quality of process outputs begins to decrease. It is necessary to develop adaptive control algorithms in order to overcome this problem.

The first objective of this thesis has been to model drying and dyeing processes and create a suitable simulation environment to be able to have an efficient and secure algorithm development period. For this reason, general concepts including characteristics of textile processes have been overviewed in the first place. Then, composite process models have been created, in which model parameters have been identified via real process data and verified in the simulation environment.

Afterwards, the control algorithm development procedure has started while taking previously overviewed control and process dynamics into account at the same time. First, model-based control algorithms have been developed and MPC has been selected as the model-based control approach. MPC has been designed and verified in the simulation environment. On the other hand, due to the implementation restrictions, MPC could not be applied to the actual processes in the field. Secondly, model-free control algorithms have been developed and two model-free control algorithms have been considered. At first, an adaptive PI control approach has been introduced. After examining PI/PID tunings in the literature and realizing their unsuitabilities, novel tuning methods have been presented. PI controllers tuned by the new methods have been verified in the simulation environment and their control performance has surpassed conventional control. Then, EPC, which is a completely novel control approach, has been introduced. After presenting fundamentals and design procedures, EPC has been verified in the simulation environment and it has been compared with the conventional control in the field applications. The advantages and superiorities of both control approaches have been shown by using real process outputs and performance assessment metrics. A qualitative comparison of conventional control and developed control algorithms are given in Table 6.1. By looking this table, it can be concluded that EPC is the best option to choose to control the corresponding textile processes.

Table 6.1. Qualitative comparison of the control methods.

Control Qualification	**Conventional PI**	**MPC**	**Adaptive PI**	**EPC**
Ease in Implementation	Medium	Low	High	High
Ease in Maintenance	Medium	High	High	High
Long Run Control Performance	Low	High	High	High
Cost Effectiveness	Low	High	Medium	High
Computational Power Need	Low	High	Medium	Medium

In a final conclusion, model-based and model-free control algorithms have been developed for drying and dyeing textile processes by utilising the developed process models and the created simulation environment. It has been verified that the developed control algorithms have better control performances compared to the current ones and they can be used in real textile processes.

Finally, there are some open subjects in this study for further improvements. One of them is consideration of other control variables in textile processes such as pressure and flow. A second one is the implementation of MPC for real textile processes. And the last improvement can be done on EPC by enhancing the smart move algorithm.

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