Nonlinear predictive control of a drying process using genetic algorithms

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Abstract

A nonlinear predictive control technique is developed to determine the optimal drying profile for a drying process. A complete nonlinear model of the baker’s yeast drying process is used for predicting the future control actions. To minimize the difference between the model predictions and the desired trajectory throughout finite horizon, an objective function is described. The optimization problem is solved using a genetic algorithm due to the successful overconventional optimization techniques in the applications of the complex optimization problems. The control scheme comprises a drying process, a nonlinear prediction model, an optimizer, and a genetic search block. The nonlinear predictive control method proposed in this paper is applied to the baker’s yeast drying process. The results show significant enhancement of the manufacturing quality, considerable decrease of the energy consumption and drying time, obtained by the proposed nonlinear predictive control. © 2006 ISA—The Instrumentation, Systems, and Automation Society.

Keywords: Genetic algorithm; Predictive controller; Optimization; Drying process

1. Introduction

Predictive control is a member of advanced discrete-time process control algorithms. This control algorithm is based on the use of an explicit process model to predict the manipulated variables and thus the future control actions are optimized throughout a finite horizon. To obtain a good performance, a process model describing the effects of all the different inputs on all the outputs must be developed. Besides objective function all the control goals must be included [1,2]. Linear model predictive control is suitable for processes that are not highly nonlinear. But many industrial processes have strong nonlinearities and predictive control is applied in order to provide satisfactory control results [3]. Two problems have appeared because of the introduction of nonlinearities in the predictive control. The first of the problems is that the modeling of processes is much more difficult and complex than the linear case. The second important problem in nonlinear predictive control is the solving of the optimization problem. The conventional iterative optimization methods are very sensitive to the initialization of the algorithm and usually lead to unacceptable solutions due to the convergence to local optima [4]. In recent years, several numerical search methods for optimization have been presented due to the complexity and the
Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{i,2,3,4}$</td>
<td>Parameter values in Eq. (11)</td>
</tr>
<tr>
<td>$b_{i,2,3,4}$</td>
<td>Parameter values in Eq. (11)</td>
</tr>
<tr>
<td>$c_{p,a}$</td>
<td>Heat capacities of the air (J kg$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$c_{p,m}$</td>
<td>Heat capacities of the water (J kg$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$c_{p,i}$</td>
<td>Heat capacities of the product (J kg$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$c_{p,vw}$</td>
<td>Heat capacities of the water vapor (J kg$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$d_m$</td>
<td>Moisture density (kg m$^{-3}$)</td>
</tr>
<tr>
<td>$d_s$</td>
<td>Dry solid density (kg m$^{-3}$)</td>
</tr>
<tr>
<td>$D$</td>
<td>Moisture diffusion coefficient (m$^2$ s$^{-1}$)</td>
</tr>
<tr>
<td>$E_{a,i}$</td>
<td>Activation energy (J mol$^{-1}$)</td>
</tr>
<tr>
<td>$J$</td>
<td>Overall objective function</td>
</tr>
<tr>
<td>$J_E$</td>
<td>Energy cost function (J s$^{-1}$)</td>
</tr>
<tr>
<td>$j_{m,i}$</td>
<td>Moisture flux at the interface (kg m$^{-2}$ s$^{-1}$)</td>
</tr>
<tr>
<td>$J_Q$</td>
<td>Objective function of product quality (kg water/kg dry solid$^{-1}$)</td>
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<tr>
<td>$j_{r,i}$</td>
<td>Heat flux at the interface (J m$^{-2}$ s$^{-1}$)</td>
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<tr>
<td>$J_S$</td>
<td>Objective function of moisture content (kg water/kg dry solid$^{-1}$)</td>
</tr>
<tr>
<td>$k$</td>
<td>Mass transfer coefficient (m s$^{-1}$)</td>
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<td>$k_a$</td>
<td>Frequency factor (s$^{-1}$)</td>
</tr>
<tr>
<td>$k_c$</td>
<td>Specific rate of the product activity (s$^{-1}$)</td>
</tr>
<tr>
<td>$L$</td>
<td>Length of the cylindrical granule (mm)</td>
</tr>
<tr>
<td>$L_N$</td>
<td>Length of chromosomes</td>
</tr>
<tr>
<td>$N_c$</td>
<td>Control horizon</td>
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<tr>
<td>$N_p$</td>
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<td>$p,q$</td>
<td>Parameter values in Eq. (11) and weighting matrices</td>
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<tr>
<td>$p_c$</td>
<td>Probability value of crossover operator</td>
</tr>
<tr>
<td>$p_m$</td>
<td>Probability value of mutation operator</td>
</tr>
<tr>
<td>$p_s$</td>
<td>Population size</td>
</tr>
<tr>
<td>$Q$</td>
<td>Product activity (kg water/kg dry solid$^{-1}$)</td>
</tr>
<tr>
<td>$Q_d$</td>
<td>Desired quality value (kg water/kg dry solid$^{-1}$)</td>
</tr>
<tr>
<td>$q$</td>
<td>N step delay</td>
</tr>
<tr>
<td>$r$</td>
<td>Radial coordinate (mm) and reference</td>
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<tr>
<td>$R$</td>
<td>Gas constant (8.314 J mol$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$R_0$</td>
<td>Initial radius (mm)</td>
</tr>
<tr>
<td>$R_d$</td>
<td>Radius (mm)</td>
</tr>
<tr>
<td>$u_a$</td>
<td>Air flow rate (kg s$^{-1}$)</td>
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<td>$U_e$</td>
<td>Number of manipulated variables</td>
</tr>
<tr>
<td>$t$</td>
<td>Time (s)</td>
</tr>
<tr>
<td>$T$</td>
<td>Temperature (K)</td>
</tr>
<tr>
<td>$T_0$</td>
<td>Initial temperature (K)</td>
</tr>
<tr>
<td>$T_a$</td>
<td>Air temperature (K)</td>
</tr>
<tr>
<td>$V$</td>
<td>Volume of the granule (m$^3$)</td>
</tr>
<tr>
<td>$V_m$</td>
<td>Volume of the moisture in granule (m$^3$)</td>
</tr>
<tr>
<td>$V_s$</td>
<td>Volume of the dry solid in granule (m$^3$)</td>
</tr>
<tr>
<td>$v$</td>
<td>Geometry factor</td>
</tr>
<tr>
<td>$X$</td>
<td>Moisture content (kg water/kg dry solid$^{-1}$)</td>
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<tr>
<td>$X_0$</td>
<td>Initial moisture content (kg water/kg dry solid$^{-1}$)</td>
</tr>
<tr>
<td>$X_d$</td>
<td>Desired moisture content (kg water/kg dry solid$^{-1}$)</td>
</tr>
<tr>
<td>$X$</td>
<td>Average moisture content (kg water/kg dry solid$^{-1}$)</td>
</tr>
<tr>
<td>$Y_a$</td>
<td>Humidity of air (kg water vapor/kg dry air$^{-1}$)</td>
</tr>
<tr>
<td>$Y_p$</td>
<td>Number of output variable</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Heat transfer coefficient (J m$^{-2}$ s$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Weighting factor in the energy cost function</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Weighting factor in $J_X$</td>
</tr>
<tr>
<td>$\rho_m$</td>
<td>Moisture concentration (kg m$^{-3}$)</td>
</tr>
<tr>
<td>$\rho_s$</td>
<td>Dry solid concentration (kg m$^{-3}$)</td>
</tr>
<tr>
<td>$\rho_m$</td>
<td>Average moisture concentration (kg m$^{-3}$)</td>
</tr>
<tr>
<td>$\rho_s$</td>
<td>Average dry solid concentration (kg m$^{-3}$)</td>
</tr>
<tr>
<td>$\rho_{vw,i}$</td>
<td>Water vapor concentration at the interface (kg water vapor m$^{-3}$)</td>
</tr>
<tr>
<td>$\rho_{vw,b}$</td>
<td>Water vapor concentration in the bulk air (kg water vapor m$^{-3}$)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Thermal conductivity of the granule (J m$^{-1}$ s$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Shrinkage coefficient</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Weighting factor in $J_Q$</td>
</tr>
<tr>
<td>$\Delta H_v$</td>
<td>Evaporation enthalpy of water (J kg$^{-1}$)</td>
</tr>
</tbody>
</table>

A number of studies to incorporate genetic algorithm-based optimization for the predictive control have been reported in the literature: Goggos and King [18] presented a design of the predictive controller based on a stochastic search technique using genetic algorithms. Doma et al. [19] developed a model predictive controller for multiple-input multiple-output processes using genetic algorithms and applied them to an industrial
distillation tower. Fuzzy model predictive control using genetic algorithms is proposed by Sarimveis, Bafas [1] and this method is illustrated via the application to a nonlinear single-input single-output reactor. Rauch and Harremoes [20] utilized genetic algorithms in real time control applied to minimize transient pollution from urban wastewater systems. A genetic optimization algorithm proposed by Haber et al. [21] is used both for the optimal length of the horizons and for the best allocation of the points in the horizons. Garg et al. [22] developed an on-line optimization using GA for the bulk polymerization of free radical systems. In a study about on-line optimizing control, presented by Mankat et al. [23], a genetic algorithm is utilized to compute the temperature in a short period of 2 min of real time.

In the biomass product drying processes, the most important indicators are energy consumption, total drying period, and the quality of product at the end of the process [24–27]. At high temperatures, the drying was run in a short time and the cost of the process can be reduced but also product quality is reduced too. For this reason, the best product quality cannot be obtained in many cases. The quality concept can be defined as a function of either moisture content or temperature or both of them in the food drying process [25,26,28]. In the literature, many optimization methods for the drying process have been presented [24,26,29].

The objective of this study is to develop a control procedure for a nonlinear drying process. The target of the proposed control algorithm can be to increase the quality of the dried end product and decrease the energy consumption during drying. A search method based on the genetic algorithm is used for the solution of the optimization problem in this paper. In Section 6, the results are discussed and proposed control method illustrated via the application to the nonlinear drying process throughout different control horizons for cylindrical and spherical granules. The paper ends with concluding remarks.

2. The model of drying process

The modeling of the drying process for the biological materials consists of four parts: moisture diffusion equation, heat balance equation, the product activity, and the shrinking equations in the granules. The model also includes dependence of the moisture and temperature of granules on several parameters like moisture diffusion coefficient, heat and mass transfer coefficients, and water activity [30,31].

2.1. Moisture diffusion equation

A generalized formulation of the moisture diffusion equation for a granule is given by the following relation [32]:

$$\frac{\partial (\rho_t X)}{\partial t} = \frac{1}{r^2} \frac{\partial}{\partial r} \left( r^2 \rho_t D \frac{\partial X}{\partial r} \right),$$

where $X$ (kg water/kg dry solid) is the moisture content inside the granule, $D$ (m² s⁻¹) is the moisture diffusion coefficient which is the function of the material's moisture content ($X$) and temperature ($T$) and $u$ represents geometry factor with $u=0$ slab, $u=1$ cylinder, $u=2$ sphere. The moisture diffusion equation is a nonlinear partial differential equation. The initial and boundary conditions are given by

$$t = 0 \Rightarrow 0 \leq r \leq R_d \Rightarrow X(0,r) = X_0,$$

$$t > 0 \Rightarrow \left. \frac{\partial X}{\partial r} \right|_{r=0} = 0,$$

$$t > 0 \Rightarrow r = R_d \Rightarrow j_{m,i} = -D \rho_t \left. \frac{\partial X}{\partial r} \right|_{r=R_d} = k(\rho_{w,i} - \rho_{w,g}),$$

where $j_{m,i}$ represents the moisture flux at the interface, $k$ is the liquid film mass transfer coefficient around the granule, $\rho_{w,i}$ is the water vapor concentration at the interface, and $\rho_{w,g}$ is the water vapor concentration in the bulk air.
2.2. Heat balance equation

The heat balance can be described as heat transfer both to and from the surface and within the material. The equation of the heat balance for a granule with general geometry is expressed by the following nonlinear partial differential equation [30,31,33],

\[
\frac{\partial T}{\partial t} (\rho_e c_{p,e} + \rho_m c_{p,m}) = \frac{1}{r^2} \frac{\partial}{\partial r} \left( r^2 \lambda \frac{\partial T}{\partial r} \right),
\]

where \( T \) is the temperature, \( \rho_m \) is the moisture concentration, \( \rho_s \) is the dry solid concentration inside the granule, \( c_{p,e} \) and \( c_{p,m} \) are the heat capacities of the product and water, and \( \lambda \) is the thermal conductivity of the granule. The initial and boundary condition are given by

\[
t = 0 \Rightarrow 0 \leq r \leq R_d \Rightarrow T(0,r) = T_0,
\]

\[
t > 0 \Rightarrow \left. \frac{\partial T}{\partial r} \right|_{r=0} = 0,
\]

where \( T_j \) is the heat flux at the interface, \( \alpha \) is the heat transfer coefficient, \( T_a \) is the incoming air temperature and \( \Delta H_v \) is the evaporation enthalpy of water.

2.3. Product activity

The product activity can be described with first-order kinetics as [28]

\[
\frac{dQ}{dt} = -k_e Q,
\]

where \( Q \) is the product activity and \( k_e \) is the specific rate of the product activity. According to the Arrhenius equation, the general rate of the product activity can be written as a function of the temperature [34]

\[
k_e = k_o \exp \left( \frac{-E_{a,l}}{RT} \right),
\]

where \( k_o \) is the frequency factor and \( E_{a,l} \) is the activation energy. The relation of the natural logarithm of the specific rate of the product activity \( \ln(k_e) \) with the temperature and the moisture content can be described by the following equation [28]:

\[
\ln(k_e) = \left[ \left( a_1 - \frac{a_2}{RT} \right) X + \left( b_1 - \frac{b_2}{RT} \right) \right] + \ln(ke),
\]

where \( p, q, a_i, \) and \( b_i \) are the parameter values in the equation. If \( p < 0 \) and \( q \geq 1 \), at high moisture content, \( \exp(pX) = 0 \) and \( \ln(ke) \) consists of the linear sum of the two parts; at low moisture content, \( \exp(pX) \approx 1 \) and \( \ln(ke) \) is described with the first linear part of the equation. The other parameters in the model have been represented in the study of Yüzgeç et al. [31].

2.4. Shrinking equations

The volume of the granule consists of volumes of both moisture and solid

\[
V = V_m + V_s.
\]

According to Coumans [35], the volume of the granule is a linear function of the average moisture content \( \bar{X} \) during shrinking that is expressed by

\[
V = V_s (1 + \tau \frac{d_s}{d_m} \bar{X}),
\]

where \( \tau \) is the shrinkage coefficient within \( 0 \leq \tau \leq 1 \). The solid mass balance is given by Eq. (14)

\[
\bar{\rho}_s V = d_s V_s,
\]

where \( \bar{\rho}_s \) is the average of the solid mass concentration. If \( V_s \) from Eq. (13) can be replaced into Eq. (14), then Eq. (15) is found

\[
\bar{\rho}_s = \frac{1}{d_s + \tau \frac{d_s}{d_m} \bar{X}}.
\]

The average of the moisture concentration \( \bar{\rho}_m \) is given by
The granule diameter can be considered as a function of the shrinkage coefficient and average moisture content and is described by the following equation:

$$R_d = R_0 \left( \frac{d_m + \tau d \bar{X}}{d_m + \tau_d \bar{X}_0} \right)^{0.5}.$$  \hspace{1cm} (17)

The average values for the moisture content and temperature in the granule are determined by an integral over the geometry defined, respectively,

$$\bar{X} = \frac{1}{\pi R_d^2 L} \int_0^{R_d} 2 \pi r L X(r) dr,$$  \hspace{1cm} (18)

$$\bar{T} = \frac{3}{4 \pi R_d^2} \int_0^{R_d} 4 \pi r^2 T(r) dr \quad \text{for cylinder},$$

$$\bar{X} = \frac{3}{4 \pi R_d^3} \int_0^{R_d} 4 \pi r^2 X(r) dr,$$  \hspace{1cm} (19)

$$\bar{T} = \frac{3}{4 \pi R_d^3} \int_0^{R_d} 4 \pi r^2 T(r) dr \quad \text{for sphere},$$

where $L$ is the length of cylinder.

### 3. Determination of the cost function for the drying process

The most important aspects of optimization of drying processes are energy consumption, total drying period, and product quality [25]. In optimization computations, first, it is necessary that an objective function is determined. The energy cost of air during drying can be expressed as the following equation:

$$J_E = \int_0^{t_d} \alpha u_a T_a(c_{p,a} + c_{p,wv} Y_a) dt,$$  \hspace{1cm} (20)

where $u_a$ is the air flow rate (kg s$^{-1}$), $T_a$ is the air temperature (K), $c_{p,a}$ and $c_{p,wv}$, respectively, represent heat capacity of air and water vapor (J kg$^{-1}$ K$^{-1}$), $Y_a$ is humidity of air (kg water vapor/kg dry air$^{-1}$), $t_d$ is the drying time, and $\alpha$ is weighting factor in the objective function.

The main purpose of the drying process is to reduce the moisture content inside the product below a desired level. For this reason, a cost function that depends on the average moisture content can be described by

$$J_X = \beta (\bar{X} - X_d),$$  \hspace{1cm} (21)

where $\bar{X}$ is average moisture content (kg water/kg dry solid$^{-1}$), $X_d$ is desired moisture content, and $\beta$ is weighting factor in the cost function of moisture content. In the food industry, the profit of the drying process is indicated by the amount and quality of the dried end product. The objective function of the product quality is given by the following equation:

$$J_Q = \gamma (Q_d - Q),$$  \hspace{1cm} (22)

where $Q$ represent product quality or the product activity, $Q_d$ is the desired quality value (100%), and $\gamma$ is the weighing factor in the cost function of the product quality. A multiobjective function can be described by the total of energy, product quality, and moisture content cost functions. This overall objective function is written as Eq. (15)

$$J = J_E + J_X + J_Q,$$  \hspace{1cm} (23)

Sensitivity of the objective function for the manipulated variables $T_a$ and $Y_a$ is shown in Fig. 1, as the results of the static optimization simulation. According to this figure, the best air temperature for drying process approximately is obtained as 70 °C.

The objective of the optimization procedure is to find the local or global minimal point by manipulated variables. The optimization problem can be described by the following equation:

$$\min_{T_a, Y_a} J(T_a, Y_a)$$  \hspace{1cm} (24)

$$J = \int_0^{t_d} \alpha u_a T_a(c_{p,a} + c_{p,wv} Y_a) dt + \beta (\bar{X} - X_d) + \gamma (Q_d - Q).$$

and the manipulated variables constraints

$$293 \text{ K} \leq T_a \leq 373 \text{ K}$$

$$0 \leq Y_a \leq 5 \text{ g water vapor/kg dry air}$$  \hspace{1cm} (26)
4. Genetic algorithms to solve optimization problem

GA are fundamentally different from the classic optimization algorithms. A genetic algorithm is a probabilistic search technique that has its roots in the principles of genetics [36]. In the GA method, the first step is to describe the length of genetic strings called chromosomes. Each chromosome consists of elements from a chosen set of symbols called the alphabet. A common used alphabet is binary strings. Each chromosome has got a value of the objective function called the fitness of the chromosome. After the choice of chromosome length, alphabet, and encoding, the first population of chromosomes is determined by a random selection of a set of chromosomes.

The second step is the selection of individuals in the population. The selection procedure to produce successive generations plays an extremely important role in a GA. In this stage, a probabilistic selection is performed based on the fitness of individuals in the population and the better individuals have an increased chance of being selected. An individual in the population can be selected more than once with all individuals having a chance of

Fig. 2. Simple genetic operators: crossover and mutation.

Fig. 3. Block diagram of the nonlinear predictive control of a drying process.
being selected. There are several schemes for the selection process: roulette wheel selection, ranking methods, and tournament selection [8,37].

After selection operation, the genetic operators are used to create new solutions based on existing solutions in the population. There are two basic types of operators: crossover and mutation. The crossover operation takes a pair of chromosomes, called the parents, and gives a pair of chromosomes, called offspring. Pairs of parents are chosen from the mating pool randomly as a crossover probability. Once the parents for the crossover operation have been determined, then the parents are applied to the crossover operation. In the simplest crossover operation, first a cutting point is chosen randomly between 1 and $L-1$, where $L$ is the length of the chromosomes. The crossover operation then involves exchanging substrings of the parents to the left of the cutting point. After the crossover operation, instead of the parents, their offsprings are replaced in the mating pool. In the other genetic operation, mutation takes each chromosome from the mating pool and randomly changes each symbol of the chromosome with a given mutation probability. If the binary alphabet is used in GA then each bit is replaced with a mutation probability from 0 to 1. Generally, the value of the mutation probability is chosen to be very small, so that only a few symbols of the chromosome are modified due to the mutation. Use of the genetic operators on the chromosomes is shown in Fig. 2.

In GA to reach a minimum or maximum point for optimization, evolution and selection procedures are repeated iteratively. GA are finished when the fitness for the best chromosome does not change significantly from iteration to iteration, or when the number of iterations reach a specified value.

5. Nonlinear predictive control based genetic algorithms of drying process

Nonlinear predictive control is an open loop control design procedure based on obtaining nonlinear model outputs of the drying process and predicting future outputs. It is based on three main

![Fig. 4. The control actions for the realized experiments in the product scale drying process.](image)
concepts [38,39]: First of all, it is the development of a model explicitly to predict the process output. The second concept is the computation of a sequence of future control actions by minimizing a given objective function. The last is the use of a receding horizon strategy. The horizons are moved from one sample period towards the future, and this procedure is repeated at each sampling period. These predictions are used to compute the control action $u_{k,t}$ by minimizing an objective function $J$, defined over a prediction horizon $N_p$ as follows:

$$J = \sum_{i=1}^{N_p} \sum_{j=1}^{N_c} p_{li,j} (r_{li,j} - y_{li,j})^2 + \sum_{k=1}^{U_c} \sum_{j=1}^{N_c} q_{k} \Delta u_{k,t}^2.$$  

(27)

Eq. (27) presents a general expression of the predictive control structure and in this equation, $Y_p$.

Table 2
The nonlinear predictive control simulation results in different control horizons for cylindrical baker's yeast granule.

<table>
<thead>
<tr>
<th>$N$ (min)</th>
<th>$Q$ (%)</th>
<th>$J_\phi$ (kJ)</th>
<th>$t$ (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>98.5103</td>
<td>2.008.900</td>
<td>1757</td>
</tr>
<tr>
<td>2</td>
<td>97.8126</td>
<td>1.642.400</td>
<td>1369</td>
</tr>
<tr>
<td>3</td>
<td>98.0032</td>
<td>1.692.500</td>
<td>1421</td>
</tr>
<tr>
<td>5</td>
<td>97.8068</td>
<td>1.683.700</td>
<td>1411</td>
</tr>
<tr>
<td>10</td>
<td>98.1463</td>
<td>1.813.500</td>
<td>1545</td>
</tr>
</tbody>
</table>

Table 3
The simulation results of nonlinear predictive control of drying process for spherical granule in control horizons with 10 and 15 min.

<table>
<thead>
<tr>
<th>$N$ (min)</th>
<th>$Q$ (%)</th>
<th>$J_\phi$ (kJ)</th>
<th>$t$ (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>94.5115</td>
<td>11.535.000</td>
<td>9713</td>
</tr>
<tr>
<td>15</td>
<td>94.2801</td>
<td>11.432.000</td>
<td>9585</td>
</tr>
</tbody>
</table>
as presented in Eq. (24), due to the effect of air energy cost.

The block diagram of nonlinear predictive control of a drying process using GA is shown in Fig. 3. The diagram consists of two basis parts: nonlinear predictive control and drying process. The nonlinear predictive control block contains a genetic search algorithm and $N$ step prediction model. In Fig. 3, $p_m$, $p_c$, $p_s$, $N$, and $q^{-N}$ represent the probability value of mutation operator, probability value of crossover operator, population size, control horizon, and $N$ step delay, respectively.

As can be seen from this block diagram, the $N$ step prediction model is operated for $p_s$ times and the output of the prediction model is obtained as them $p_s \times 1$ vector. The predicted model outputs are used to calculate the value of the objective function known as fitness in GA and then the next generation is formed using the selection and evolution procedure. These procedures are operated around the loop until the GA stop. At the end of the genetic search algorithm, the optimization

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**Fig. 6.** The responses of the nonlinear predictive controller in control horizons with 10 and 15 min for spherical granule.

$U_c$ are the number of output and manipulated variables, respectively, $r$ is the reference, $y$ is the predicted output, and $p$, $q$ are the weighing matrices. In this study, the objective function has been used

**Fig. 7.** Trajectory of manipulated variable $T_a$ and simulation resulting average moisture content, average temperature, and product quality for cylindrical (a) and spherical (b) granules.
problem is solved and the outputs of the nonlinear predictive controller as control inputs are applied to the drying process.

6. Results and discussion

For the drying process, two kinds of granule forms are used: cylindrical and spherical form. The baker yeast, the microorganism *Saccharomyces cerevisiae* was used for the experimental data of the drying process in this study. The GA parameters were established by a trial procedure. The stopping criterion of the GA optimization is that the fitness for the best chromosome does not change significantly from iteration to iteration. The parameters of GA used to solve the optimization problem are given in Table 1. For selection method is chosen tournament procedure and both of genetic operators are used to find the minimal value in optimization. The parameters of drying process of the baker's yeast were taken as \( X_0 = 1.563 \text{ kg water kg dry solid}^{-1} \), \( R_0 = 0.5 \text{ mm} \), \( T_a \approx 373 \text{ K} \), \( u_a = 12000 \text{ kg air h}^{-1} \), \( \tau = 0.3 \) for cylindrical granule and \( X_0 = 1.7 \text{ kg water kg dry solid}^{-1} \), \( R_0 = 1.5 \text{ mm} \), \( T_a \approx 373 \text{ K} \), \( u_a = 12000 \text{ kg air h}^{-1} \), \( \tau = 0.6 \) for spherical granule. The drying model has been run for these parameters and the energy cost of air during drying has been calculated as 1.944.500 kJ for cylindrical granule and as 14.243.000 kJ for spherical granule.

The air inlet temperature was maintained at 100 °C as shown in Fig. 4 during most parts of the drying process. The values of temperature and humidity of the air at the inlet and outlet and its flow rate were measured on-line and registered on a computer in order to establish continuous material and energy balances for the prediction of the moisture content and temperature of the product [40]. The details will not be disclosed here due to the secrecy of the information. The total drying periods have been measured as 27 and 206 min for cylindrical and spherical granules, respectively. The quality of the dried end product has been obtained as 89.6% for the cylindrical granule and as 86% for the spherical granule.

The responses of the nonlinear predictive controller in different control horizons for the cylindrical granule are shown in Fig. 5. The product
For cylindrical and spherical granules, the trajectory of the manipulated variables \((N=2 \text{ min} \text{ and } N=15 \text{ min})\) and the average moisture content, average temperature, and product quality are shown in Fig. 7. The effect of disturbance was presented in Fig. 8 for the cylindrical granule. In this figure, the input variables \((T_a\text{ and } Y_a)\) have been chosen as the best result obtained in the control simulations. The disturbance sign has been used as \(0.5u(t-600)\). In response of the drying process, after 600 s, the average temperature increases excessively from 27 to 48 °C. On the contrary, the product quality decreases from 98% to 38%. Because of the increase in the temperature, the value of the desired moisture content is reached more rapidly than the normal condition. The reason for using the exponential transition instead of the sharp transition among the steps in the air temperature profile is that there is not a sharp transition in the real time production scale drying process.

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In Fig. 9, the control actions calculated by the nonlinear predictive controller and the outputs of the drying process were showed in the effect of the disturbance for the cylindrical granule. The
product quality has fallen down 38% in Fig. 8, holding on to 80% by the nonlinear predictive control. This is a very important point especially in the drying process of the biologic product. Besides, the increase in the temperature is limited by this controller. Thus the capability of the proposed control algorithm is presented for the disturbance example.

7. Conclusions

A control procedure based on genetic algorithms is developed for a biomass drying process known as nonlinear. In this study, it is used as a search method based on the genetic algorithm because of the complexity of the optimization problem. The proposed control algorithm predicts both of the manipulated variables. The effects of the prediction are shown clearly using different control horizons in the simulations. The simulation results show that the performance of the drying process will be increased by this proposed study. In the food industry, these control results expose very important points. One of these points is the reduction of the total drying period and energy consumption. The other one is the improvement of the product quality. The proposed control algorithm can be easily adapted to other batch processes.

The genetic search algorithms can be employed for real time applications in the nonlinear predictive control. But in these applications, there is a main drawback. This drawback is that on-line GAs need a certain number of generations to converge, so that they cannot be practical to systems with short times. However, there is a considerable scope for the development of further and more powerful algorithms, since the high computational speed and the improved performance of these new algorithms will increase the practicability of online GAs towards systems with shorter times [10].

References

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