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Online optimisation of fruit drying based on drying curve identification.

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Abstract

Drying optimisation is of great interest for food industry both in economic terms (energetic cost) and from an organoleptic point of view (product quality). Dryers are designed to extract the water out of the product while preserving its qualities of interest. Although both optimisation of the heat production system and the drying chamber can be considered separately, it is useful for the industry to be able to globally supervise the production system and reduce the drying time despite the local optimised technical solution already available. Required performances (qualities in terms of moisture rate, operating time...) can be achieved within a correct estimation of the fruit moisture in order to configure control set points. The methods suggested in this paper are based on thermodynamical knowledge on water exchange in order to achieve an online identification of the drying curve mathematical model using a set of known data at the current time. Such model can allow further prediction of drying duration and control adaptation but also the qualification of the original product that might differ from one production to another because of fruit maturity or origin for instance. In this paper, no prior knowledge of the raw material to dry is required (except part of process history) to perform model identification and selection (within quadratic programming, parametric estimation or interpolation under correct assumptions). Of course constraints as maximal temperature supported by the fruit and the dryer limitations should be taken into account to proceed to a two-step drying (pre-drying and drying at higher temperature) to achieve the performances. Despite the simplicity of the model, the proposed algorithms are sufficient to allow the detection of a change in the fruit structure due to the loss of water; that results in a modification of water activity. Although the application is made on a laboratory incubator with great limitation of the control, the method is to be transposable on any dryers of industrial scale with the advantage that it requires only a limited number of measurements.

Keywords: fruit drying, mathematical model, identification, optimisation.

1. Introduction

Fruits and vegetables can be preserved and treated within drying. Dryers make it possible to convert perishable goods into stabilized products lowering water activity (a_w) down to a value below 0,5 (Bonazzi and al., 2003); dryings concentrate nutrients of food product to allow conservation and increase extension of consumption dead-line. Due to food product brittleness (fruit) and induced cost of drying, industrials should optimise dryer design to achieve the performances (desired constant moisture in the final product, guarantee of production time). Based on System Analysis and Design Technic description (Lissandre, 1990) dryers can be described within three functional sub-systems (functional blocks) that should be optimised locally (Nuninger and al., 2006):

1. Heat quantity production (with pre-heater) to reduce calorific production cost (Teeboonma and al., 2003; Achiaviriya and al., 2000);
2. drying chamber (with dynamic fluid and dynamic or fixed product (Mujumdar, 1995)) to reduced

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energetic cost per unity of evaporated water (Bonazzi and al., 2003);

3. supervision task in charge of global optimisation within correct temperature profile: *i.e.* control reconfiguration depending on online model identification and switching time decision under robustness considerations with respect to model uncertainties (shape, maturity, conformation of fruits, product structure modification during time evolution).

In this paper, for a given dryer, the focus is put on the upper supervision level that implement a 2-step drying of given temperature gradient with online adapted temperature switching time (*i.e.* pre-drying at relatively low temperature followed by a drying at higher temperature during a shorter period to avoid possible product damages). Due to brittleness of the product, a compromise should be found for step duration and temperature gradient: indeed too small a temperature will increase the drying duration that might result in a loss of quality (colour changes due to the increase of non-enzymatic and enzymatic oxidations) while a too high temperature will destroy the fruit structure and its composition (vitamins...) but reduces response time. Nevertheless, to finish drying by a heat-stroke (high increase of the temperature) will help the extraction of the remaining water in the product; made less extractable because of fruit structure modification (more porous product due to water loss). One technical solution is designed with plate-dryers. For a given temperature T, the fruit drying plot follows a decreasing exponential curve given by mathematical Model (1) with time-constant ($\tau = 1/k > 0$) depending on drying temperature T(t) and fruit structure (Lewis, 1921; Mujumdar, 1995). Models (1) based on drying at constant temperature (see part 3) are plotted on Figure 1(left) that shows that τ is no-constant and greater for increasing temperature.

Table 1 gives the identified parameter k of these models with the validation criteria: reconstruction error statistics and minimal quadratic error criterion J (8). For a given model, cross-validation was made using 2-step drying data to compute J. Corresponding drying curves are given on Figure 1(right).

$$y(t) = ye + (y_0 - ye)e^{-k(t-t_0)} = a + b.e^{-k(t-t_0)} > 0 \text{ with } k > 0, y_0 = y(t_0) \text{ and } ye = \lim_{t \rightarrow \infty} y(t) \quad (1)$$

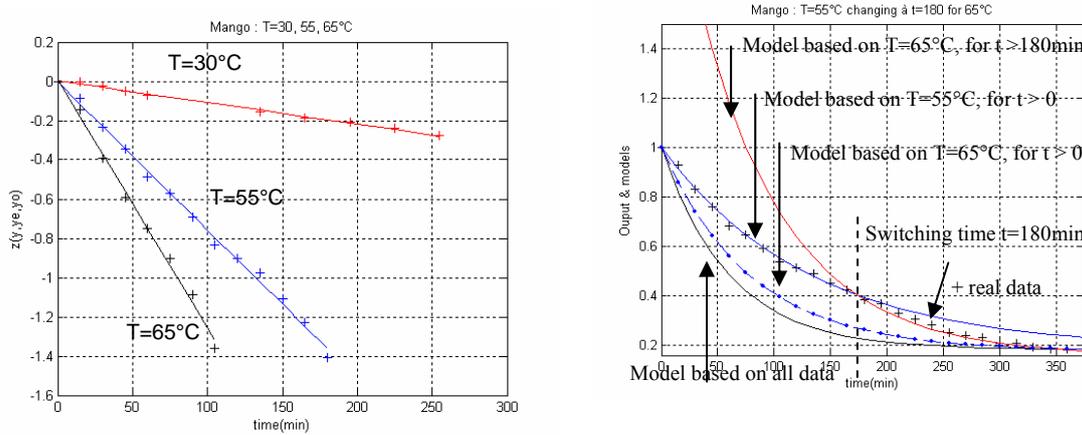


Figure 1. (left) For mango drying at constant temperature, Model (1) identification based on Least square method (7) (right) Drying curve Model (1) for 2-step drying of mango (55°C with change to 65°C at time 180min) (Table 1).

$$X(t) = \lambda \cdot \beta \cdot a_w(t) / (1 - \lambda \cdot a_w(t)) / (1 - \lambda \cdot a_w + \beta \cdot \lambda \cdot a_w(t)) \quad (\text{BET model for } \lambda=1) \quad (2)$$

$$X(t) = \alpha \cdot (a_w / (1 - a_w))^\beta \quad a_w(t) = \exp(\alpha / R \cdot T \cdot X^r) \text{ with } R=8.314 \text{ J} \cdot \text{mol}^{-1} \cdot \text{K}^{-1} \quad (3-4)$$

$$X(t) = \alpha + \beta \cdot \log(1 - a_w(t)) \quad X(t) = (-\ln(1 - a_w) / \alpha)^{1/\beta} \quad (5-6)$$

with R the universal gas constant, T the temperature in Kelvin and $\alpha, \beta, \lambda, r$ parameters to be identified. At the price of a larger complexity some models connect the evolution of k to internal structure modifications of the fruit (that results from water loss, air flow and external air moisture variations) characterized by water activity parameter $0 < a_w(t, T) < 1$.

Table 1. Identified parameter k for given (y_0, y_e) . Validation criteria: minimal quadratic error criterion J (8), error mean and standard deviation. Cross validation is criterion J computed for given model and 2-step drying data.

Drying	T (°C)	k (HH:MM) (15:07)	Y o	Ye	Validation (J)	Cross validation	Error mean	Error Std.
Constant T	30	0.0011 (15:07)	1	0.271	0.0017	-	-	-
Constant T	55	0.0076 (02:12)	1	0.185	0.0013	J= 0.030	0.224	0.0260
Constant T	65	0.0126 (01:19)	1	0.178	9.4246e-006	J= 0.257	-0.080	0.060
2-step	55,65	0.0166 (01:00)	1	0.184	0.9273	J=0.518	-0.1133	0.090

Unfortunately for industrial application no online measurement of a_w is available but black-box models connected to the product moisture content $X(t)$ exist (Chung and al., 1967; Al-Muhtaseb and al., 2000; Sudhamani and al., 2005): Guggenheim-Anderson-de-Boer (GAB) Equation (2) (DeBoer, 1953) reduced to Brunauer-Emmet-Teller (BET) model for $\lambda=1$ (Brunauer and al., 1938), (Oswin, 1946) Equation (3), (Hasley, 1948) Equation (4), (Smith, 1947) Equation (5), (Henderson, 1952) Equation (6). Nevertheless, such models require off-line identification based on specific experimentations (due to the dry-matter parameter that defines moisture rate) which does not fit the assumption of our work: identification with no prior knowledge on the fruit ($0.1 < a_w(t, T) < 0.85$). Note that such a simpler Model structure as (1) (Mujumdar, 1995) is sufficient for fixed drying conditions and short drying period; when pair (k, y_e) can be considered as constant. As a consequence, Model (1) can be rewritten as the linear Model (7) for known initial condition. Linear regression in the least square sense leads to k identification as illustrated on Figure 1(left). But experimental conditions might be hard to reproduce due to industrial perturbations of process and fruit quality variations (maturity). However average values for k are obtained, the equilibrium value might be inaccurate for longer drying time. That is the reason why improvements are made in the following, based on online identification of pair (k, y_e) over an observation window and further adaptation of the model by optimal selection that does not require specific experiments.

$$z(t, y_0, y_e) = \ln \left(\frac{y(t) - y_e}{y_0 - y_e} \right) = -k(t - t_0) = a.t + b \quad (7)$$

In the following, drying curve modelling and identification based on the three parameters (k, y_0, y_e) Model structure (1) are considered. Three online methods are presented for parameters estimation that will be further compared in case of switching time decision: interpolation based on 3 data chosen upon a set of available measurement at a given time, quadratic programming based on a sliding window of finite memory and finally algebraic estimation (Sira-Ramirez, 2006) that gives easy and quick online computation. This last method from the Automatic control field seems of great interest for online identification (Fliess and al., 2002; Fliess and al., 2003a) and state estimation techniques (Fliess and al., 2003b) based on algebraic theory independent of the peculiar model representation (Sira-Ramirez and al., 2002). Additive recursive step for model selection upon the valid ones available (under physical parameter constraints and with respect to the identification method) gives the right model for the step value estimation of the equilibrium and switching time decision based on k modification. Results are discussed for a laboratory dryer used to dry mango slices and perspectives are given.

2. Optimal online parameters identification of drying curve model

2.1 Online modelling procedure

Figure 2 describes the online modelling procedure reduced to the following steps (as the model structure is already selected as (1) with unknown parameters pair (k, y_e) and the known initial condition y_0): based on a set of data available at time t , parameters identification for all possible models is made followed by model validation (parameters should be positive) and further selection of the optimal model (minimal

quadratic error criterion for the already known data).

No pre-experimentation to get dry-matter is required for our procedure and real time computation is not a problem as drying processes are slow ones. Only weight measurements are required with normal accuracy thanks to correct procedure of weighting and apparatus.

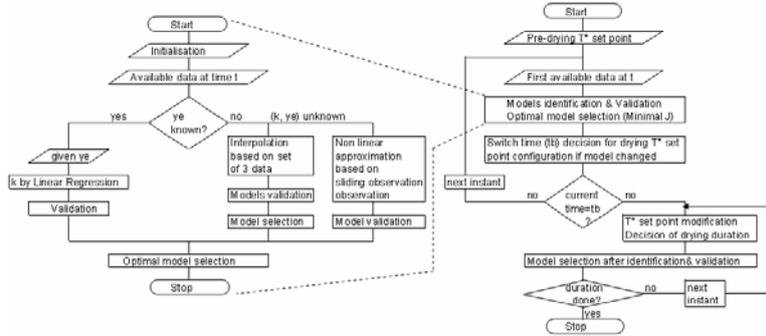


Figure 2. Procedure for optimal selection of correctly identified model. Recursive procedure for switching point decision task and model adaptation if required.

2.2 Online parameters identification based on 3 chosen data

Thanks to correctness of the Model structure (1), recursive selection of interpolated model is sufficient to follow the drying along the time and get correct estimation of the equilibrium. The interpolation of the unknown set of parameters (k , $a=ye$, $b=y_0-ye$) requires Equation (1) to be satisfied for 3 chosen measurements $y_{(i)}$ upon the $(n+1)$ available data (i from 0 to n) at current time t_n .

$C_{n+1}^3 = (n+1)! / 3!(n+1-3)!$ possible combinations exist ($n>4$), i.e. numbers of different models, upon which the optimal one should be selected considering the minimal quadratic error criterion J (8) over the interval. Such method will lead to the “best” model that satisfies a minimal J for all the process history. In the course of time, the final equilibrium prediction is a convenient piece of information for supervision to decide switching time set point for 2-step drying control. Anyway, one can consider a shorter sliding observation window to allow a better reconstruction all along the process history too.

$$J = \sum_{i=0}^n \|y(t_i) - \hat{y}(t_i)\|^2 \quad \text{where } \hat{y}(t) \text{ is the model output and } y_i=y(t_i) \text{ the measurement} \quad (8)$$

The problem can be solved in a nice way: first consider the (a,b) solution (express with respect to k) of the 2-dimensional Cramer system for two data (y_1, y_3) taken inside the current observation window $[t_0, t_n]$. Second, the identification of k is made thanks to the remaining equation to be solved for a chosen data y_2 inside the interval. Taking the limit t_0 and t_n allows a better description of data while reducing the number

of models left (for the remaining choice of data $(n+i-2)$) to $C_{n-1}^1 = n-1$ combinations (and therefore the computation cost, if necessary). The solution (a,b) is expressed as (9) for the given variable Z and integers (p,q) defined as (10). Value of k is given by the positive real solution of the polynomial equation in Z (11). Pair (a,b) is deduced afterwards. Equation (11) should be solved within non linear programming but taking the medium of the observation window as the 3rd data will reduce the problem to a 2nd order equation easier to solve.

$$(a,b) = \left(\frac{y_1 \cdot Z^p - y_3 \cdot Z}{Z^p - Z}, \frac{y_3 - y_1}{Z^p - Z} \right) \quad \text{under } y_2 = a + bZ^q = \frac{y_1 \cdot Z^p - y_3 \cdot Z}{Z^p - Z} + \frac{y_3 - y_1}{Z^p - Z} Z^q \quad (9)$$

$$\text{with } Z = e^{-k(t_1-t_0)} \Leftrightarrow k = \frac{-1}{t_1-t_0} \cdot \ln(Z) \quad \text{and } (p,q) = \left(\frac{t_3-t_0}{t_1-t_0}, \frac{t_2-t_0}{t_1-t_0} \right) > (1,1) \quad \text{as } t_0 < t_1 < t_2 < t_3 \quad (10)$$

$$(y_1 - y_2) \cdot Z^p + (y_2 - y_3) \cdot Z + (y_3 - y_1) \cdot Z^q = 0 \quad (11)$$

2.3 Online parametric estimation

Based on (Sira-Ramírez and al., 2006), the pair (k, y_e) is estimated online thanks to approximations of the successive derivatives of the observable output signal within mathematical operations based on Laplace domain. Equation (1) is considered as the solution of the first order differential Equation (12) where the input $v(t)$ stands for the influence of perturbations and drying regulation. Therefore $u(t)$ is considered as a 1-step input to get the equilibrium step (within a 1st order response), which value is defined by the pair (k, y_e) to estimate on a short window memory. Applying Laplace transform to Equation (12) allows the elimination of the unknown parameter y_e after multiplying it by s and derivation with respect to s (under the assumption that y_e is constant other the interval). Further multiplication of (13) by s^2 (that stands for a double integration in the time domain) allows the extraction of an estimation of parameter k (14) thanks to inverse Laplace transformation. Estimation of y_e is then given by s^{-2} multiplication of (12) in Laplace domain. Quality of this estimation should be improved within re-initialisation of the integration.

$$\dot{y}(t) + k.y(t) = v(t) \text{ with } : v(t) = k.y_e.u(t) \text{ is the input with 1-step } u(t) \quad (12)$$

$$2sY(s) + s^2\dot{Y}(s) - y_o = -k.Y(s) - k.s\dot{Y}(s) \quad (13)$$

$$\hat{k} = \frac{2\int_0^t y(\delta)d\delta - t.y(t) - y_o.t}{\int_0^t \delta.y(\delta).d\delta - \int_0^t \left(\int_0^\delta y(\lambda)d\lambda \right) d\delta} \text{ with } \int_0^t \int_0^{t_1} \dots \int_0^{t_{n-1}} f(x_n)dx_1 \dots dx_n = \int_0^x \frac{x-t)^{n-1}}{(n-1)!} f(t)dt \quad (14)$$

$$\hat{y}_e = 2 \cdot \left(\hat{k} \cdot \int_0^t \left(\int_0^\delta y(\lambda)d\lambda \right) d\delta + \int_0^t y(\delta)d\delta - t.y_o \right) / \left(t^2 \cdot \hat{k} \right) \quad (15)$$

2.4 Online identification based on sliding window and SQP

The unknown pair (k, y_e) in model Equation (1) is approximated for known initial condition within Sequential Quadratic Programming (SQP). The criterion to minimise by SQP is defined as the quadratic difference between the experimental data and modelling point (Schittkowski, 1986). At each instant, an approximated model is computed based on a sliding observation window. The algorithm is initialised using the prediction given by the optimal model computed upon the previous sliding window. The length of the sliding window memory is chosen thanks to several empirical tests and a 7-point length seems to be a sufficient process history to fit the experimental drying curve; a result consistent with the one on algebraic estimation that only computes a physically validated solution after 8 points of history. Future work will focus on the proof over the size of the sliding window memory based on the necessary condition for the existence of a solution (Nuninger, 1997).

3. Results

Mango slices are dried in a laboratory incubator Hereaus B20: 233 liters chamber with quick temperature regulation by PID and natural air circulation and refreshing. Drying is optimised within a 2-step drying with fixed temperatures chosen equal to 55°C for pre-drying and to 65°C for drying (lower to the 70°C limit supported by the product (Rozis and al., 1995)) and switching time set point equal to 180min. Fruits were cut into slices of square surface 150mm² by 10mm thickness (of weight 1g) orderly placed on a plate in the middle of the incubator (Catiau and al., 2006). Two essential phenomena take place simultaneously in the drying chamber: heat conduction around the fruit (due to the difference of temperatures between fruit and air) that can be neglected thanks to the shape and consistence of fruit in comparison with the time constant of the second phenomenon referred as the moisture diffusion and evaporation process (Rozis and al., 1995) that implies the drying duration. Measurements are made with sampling time equal to 15min with respect to Shannon criteria (a complete drying to reach the equilibrium at the higher temperature supported by the fruit gave us a time response of about 390min). Online identification makes us able to take into account the fruit structure modification which results in a modification of the time constant (1/k).

3.1 Results within selection of interpolated models

Models are computed based on the initial condition t_0 , the current time t_n and a 3rd point chosen between these instants in the observation window $[t_0, t_n]$. Recursive model selection allows an evolution of the parameter k that stands, at the current instant, for the more convenient model with respect to the available process history; this explains why the selected k might not be so good for shorter memory $[t_i, t_n]$ but it is correct for selected points. (k, ye) evolution is shown in Figure 3(left) that allows further delayed detection of the switching-time. Figure 3(right) shows the evolution of prediction during time leading to a model that sticks the data during all process history thanks to our selection. Figure 5(right) shows data reconstruction during time thanks to our algorithm. Comparison with the methods proposed further is obvious. To increase accuracy on a given observation window, models could be selected within quadratic error criteria based on shorter memory but final optimal model will not fit all the process history: compromise depends on the objective. Linear regression could now be correctly computed taking into account this balance value to get a model upon all the process history.

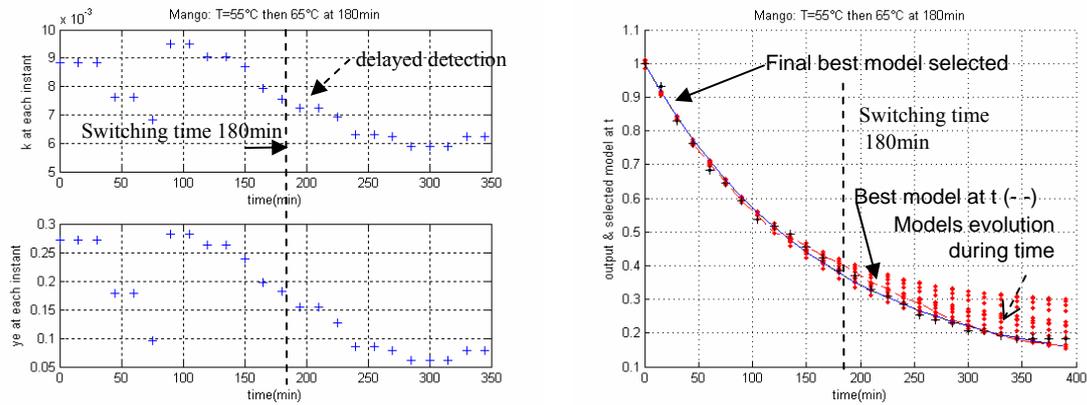


Figure 3. (left) (k, ye) evolution within model selection to fit the process history - (right) Model reconstruction (.) of data (+). Final best model (--) is given for chosen points: $t/Te = 1, 17, 22$ ($k=6.2 \cdot 10^{-3}$, $ye=0.08$, $yo=1$)

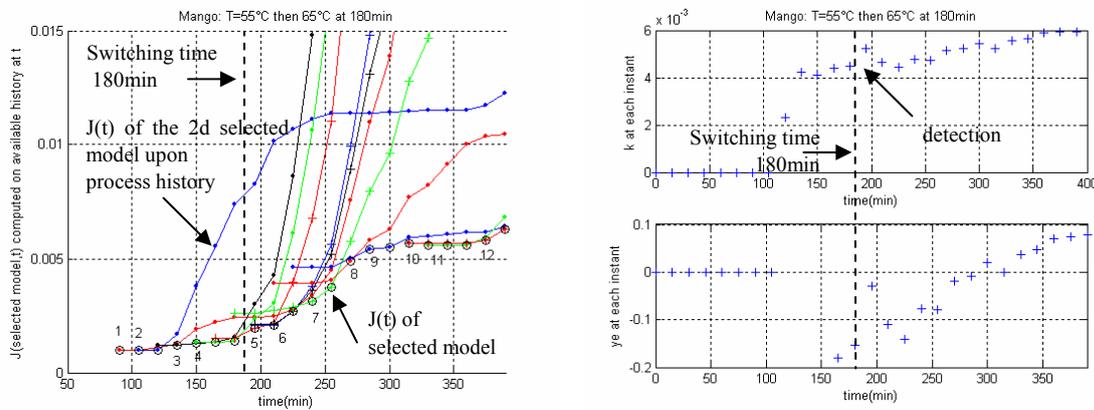


Figure 4. (left) $J(t)$ of selected models computed over all data available at t (' n° ' gives time of selection of model i) - (right) (k, ye) given by algebraic estimation (no solution under 8 points history)

Figure 4(left) gives the evolution of the criterion $J(t)$ for each selected models i (J is computed over all the process history available at t): for a selected model (optimal for the past data at t) model criterion $J(t)$ increases due to greater errors on the new data prediction as these data bring new information on the fruit structure and temperature modifications. The change of curve of J -plot for the optimal model at time of selection (numbers on the curve o) allows delayed detection of switching time.

3.2 Algebraic estimation

Figure 4(right) shows the evolution of k and ye using algebraic estimation. The method requires an 8-point process history to get validated data which is a way to choose the sliding window's length for other approximation methods like SQP. Reconstruction of the data is good as shown on Figure 5(left) however

the estimation of y_e lacks quality and might not be convenient except for final data ($k=6 \cdot 10^{-3}$, $y_e=0.0995$). Indeed, the more information we have from process history, the better the final step is computed. Data estimation could be improved within re-initialisation of integration (Sira-Ramirez and al., 2006). This will be the focus of future work to increase accuracy of (k, y_e) estimation taking into account error on data reconstruction. In addition, we note a change in k evolution around the temperature switching time that might be detected (this point is more obvious comparing the method on a single temperature drying for which one such a break does not appear). Computations were made within Matlab/Simulink and Maple.

3.3 Approximated models based on finite memory window and SQP

Figure 5(left) shows the correct reconstruction of the data that justifies the use of SQP upon sliding observation windows. Further drying process supervision and detection of fruit modification are possible based on estimation of the equilibrium y_e (Figure 5(right)). The final model ($k=8 \cdot 10^{-3}$, $y_e=0.2$) will not fit all the process history as a sliding window is used but the reconstruction is accurate for each window.

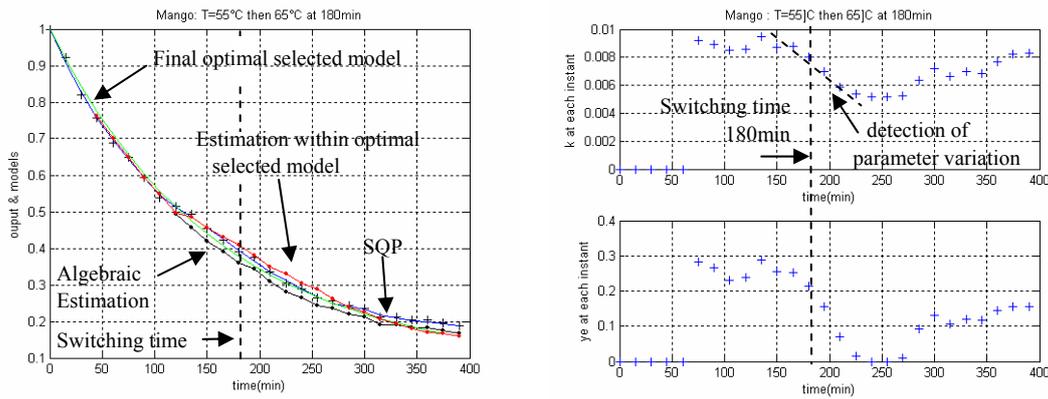


Figure 5. (left) data (+) and models with the 3 methods: SQP, Algebraic estimation and optimal model selection (right) evolution of k and y_e for SQP

3.4 Switching time decision and discussion between the methods

Switching time decision can be based on the online estimated value of y_e and the current output value. For a given rate of the final state to reach (moisture rate), one can decide to increase the temperature to end the drying while respecting fruit constraints. Upper supervision task could also consider the evolution of k and conclude on the drying perturbations that will probably lead to an incorrect drying (too long duration). Linear approximation is only acceptable if one considers a small observation window under the assumption that fruit structure and drying conditions do not change. Otherwise non linear solutions should be performed (as SQP) that improve reconstruction over the recent history thanks to a correct initialisation of the algorithm. Using interpolation and model selection is a way to get a drying curve model that best fits all the data with online adaptation as giving a correct view of final equilibrium, helping the supervision. Considering a sliding observation window (*i.e.* a shorter process memory) will give more importance at the new data in the model to better fit the curve, but detection in k will be less obvious as k modification can be compared to incipient variation. Future work should consider a new residual defined as the difference between two estimations based on overlapping history (Nuninger and al., 1997) to improve detection. Finally, algebraic estimation will be of interest in the future as it is quicker and simpler but a sliding window should be taken into account to recursively initialise the integrations in the course of time. Our work is of interest as this is not the usual way of considering drying in terms of online optimisation. This will be the aim of future works. Taking into account water activity models, we will also consider the choice of switching time (t_s) and temperature gradient (ΔT) between pre-drying and drying to control the duration of drying that will rely on non-linear optimisation over the liberty degree ΔT , t_s , $k(T, a_w)$.

4. Conclusion

Thanks to online identification of drying curve using a simple exponential model structure, our two-step drying procedure allows us to reduce the drying duration, supposing the heat production and drying chamber are already optimised as local functional blocks. We presented three methods that all show that further fruit modification detection is possible and can be improved thanks to sliding observation window and model selection. Our supervision block will compute a correct second set-point configuration that might be adjusted during drying, if required. As a consequence, it is possible to better control the production performance (duration of drying) so that production delays are better respected despite uncertainties such as fruit maturity, thickness, arrangement on the plate. However we experiment our technique on a laboratory incubator, it is sufficient to illustrate that it is of possible usefulness for industrial on a larger scale in addition of other optimisation of drying chamber and heat production process. The method is transposable and better results might be brought out using non-linear finite memory estimation and detection within a residual defined as the difference of two estimations based on intervals with common data. Our procedure is worthwhile as no prior knowledge is required on the product to dry (dry-matter is not necessary) and online computation is possible with few real time constraint as drying is a low process. Weight measurement is not such a problem as only part of the production can be used based on statistical sampling. A new method, algebraic estimation, was first tested in this field and seems to give interesting results. Further work will then focus on both the improvement of the method to get more precise estimation, and on a special residual based on detection windows for overlapping process history to detect changes in fruit structure (characterised by incipient modification of time constant). Indeed, despite the estimation of pair (k, y_e) , decision making strategies should be developed to fix the switching time and the temperature gradient set point given the initial temperature of the pre-drying and the desired performances.

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