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Scheduling of an integrated forest biorefinery using multi-parametric programming

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Implementation of an integrated forest biorefinery complicates the existing pulp and paper processes considerably and leads to even more challenging production control. Integrated forest biorefineries are cost efficient in a situation where parameters like product demand, raw material supply and prices are stable. However, these parameters vary with respect to time and are often subject to unexpected deviations. Having ways to systematically consider uncertainty is as important as having the scheduling model itself. Methodologies presented in this paper aim at producing feasible, robust, and optimal schedules - an optimization problem involving hard constraints and uncertainties, based on dynamic and multi-parametric programming techniques is presented. As a result a complete map of optimal schedules can be obtained as a function of parameters.

1. Introduction

The need to decrease the use of fossil fuels, and to find renewable raw materials for various industrial production processes, encourages examining the advantages of biorefineries. Integration with existing industrial plants reduces the capital and operating costs of making biomass products and hence also the production costs of the end products. Cost competitiveness and environmental sustainability will be key issues in future markets for biomass-based products. This paper concentrates in creating methodology for the cost efficient production scheduling of forest integrates. The processes have typically several raw materials and end products. The methods consider flexibility of production, uncertainties of supply, demand and prices of raw-materials and products. One way of proactive scheduling is using sensitivity analysis and parametric programming. These methods can offer analytical results to problems related to uncertainty. Sensitivity analysis is used to determine how a given model output depends upon the input parameters. Parametric programming serves as an analytic tool by mapping the uncertainties in the optimization problem to optimal solution alternatives. From this point of view, parametric programming provides the exact mathematical solution of the optimization problem under uncertainty.

In this paper the problem of process scheduling under uncertainty is studied using multi-parametric programming. Based on the uncertainty type (prices, demands, and processing times), the scheduling formulation results in different parametric problems

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including multi-parametric mixed integer linear (mpMILP), quadratic (mpMIQP), and general nonlinear programming (mpMINLP) problem. In the literature, the multi-parametric programming method has been mainly applied in online optimization, process control, and process synthesis (Pistikopoulos et.al., 2007a; Pistikopoulos et.al., 2007b). Multi-parametric linear programming and multi-parametric quadratic programming problems are well studied due to the relatively smaller problem complexity (Bemporad et.al., 2002; Borelli et.al., 2003). General multi-parametric nonlinear programming problem is not well addressed because the exact solution of mpNLP is very complex (Acevedo & Salgueiro, 2003). Existing multi-parametric mixed integer programming methods are based on the solution of mpLP or mpQP subproblems. (Acevedo & Pistikopoulos, 1997; Dua & Pistikopoulos, 1999). The general multi-parametric mixed integer quadratic programming is hard to solve. Dua et.al. (2002) proposed a methodology to address this problem for the special case derived from optimal control problem.

In order to study the suitability of multi-parametric programming an example case was developed. In the example case the uncertainties in product demand, raw material supply and prices are incorporated into scheduling model. The time dependency of the parameters adds dynamics into the problem. Therefore an optimization problem involving hard constraints and uncertainties, based on dynamic and multi-parametric programming techniques is presented. The profitability is studied as a function of state-transition cost Q, Eq. 3. An advantage of the proposed methodology is that the complete map of optimal schedules can be obtained as a function of parameters; rescheduling can be performed via simple function evaluations without any further optimization. Presented numerical examples illustrate the potential of the proposed methodology.

2. Description of the case and results

There are many alternatives how to execute the biorefinery concept. Concepts brought to daylight need to be operated optimally. This paper presents a generic model for the integrated biorefinery and tests the methodology for the optimization of production. At first a static case is studied and a parametric solution generated, then predictions of parameters are added and the dynamic case solved.

The example process consists of 4 sub processes. Two raw material flows are transferred into four products. There are no intermediate storages – what comes in, goes out. The operating conditions are presented in the Table 1. Figure 1. presents a flow chart of the process.

Table 1 The operating conditions of the process. The divisions of the raw material/sub product flows are defined as well as the production costs of the sub processes.

	x_1	x_2	x_3	x_4	Production cost / sub process
EP1	0,7	-	-	-	1 €/unit
EP2	0,18	-	0,6	-	0,5 €/unit
EP3	0,12	0,2	0,4	0,2	1 €/unit
EP4	-	0,8	-	0,8	2 €/unit

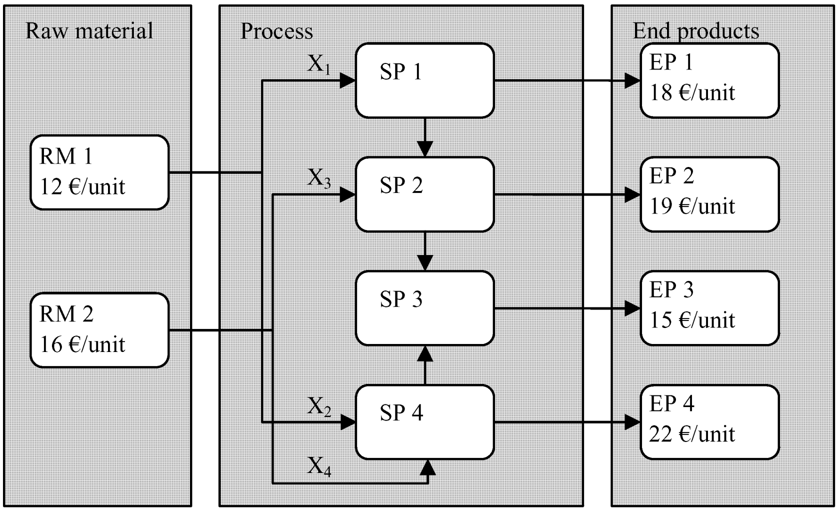

Figure 1 A flow chart of the example process.

In this case example the uncertainty is present in the raw material prices and in their availability. Now only right hand side and objective uncertainty exists, the critical region of mpLP is formed by linear inequalities. θ_1 defines the uncertainty in the raw material prices and θ_2 and θ_3 in availability. On the basis of the Eq. 1 (Li & Ierapetritou, 2007) the problem is defined with:

$$\begin{aligned}
&\min_x \left(c + D^T\theta\right)x \\
&s.t. \\
&Ax \le b + F\theta \\
&\Phi\theta \le \phi
\end{aligned} \tag{1}$$

The Eq. 2 defines the cost function and the constraints of the problem.

$$\begin{aligned}
&\min_x \left[-\left(4.82+\theta_1\right)x_1 - \left(7.6+\theta_1\right)x_2 - \left(0.9+\theta_1\right)x_3 - \left(3.6+\theta_1\right)x_4\right] \\
&s.t. \\
&x_1 + x_2 \le 25000 + \theta_2,\ x_3 + x_4 \le 15000 + \theta_3 \\
&\left.\begin{aligned}
&-a \le 0.3x_1 - x_3 \le a \\
&-b \le 0.12x_1 - 0.2x_2 + 0.4x_3 - 0.2x_4 \le b \\
&-c \le x_2 - x_4 \le c
\end{aligned}\right\} Tolerances\ for\ recipes \\
&x_1 \ge 0,\ x_2 \ge 0,\ x_3 \ge 0,\ x_4 \ge 0 \\
&0 \le \theta_1 \le 4,\ 0 \le \theta_2 \le 1500,\ 0 \le \theta_3 \le 1500
\end{aligned} \tag{2}$$

One advantage of using parametric programming techniques is that for problems such as process planning and scheduling, a complete map of all the optimal solutions can be obtained. Moreover, as the operating conditions fluctuate, the new set of conditions does not have to re-optimized since the optimal solution as a function of parameters, or the new set of conditions, is already available.

As a result of the optimization a complete map of all the optimal solutions is available, Table 2. presents profit and raw material flow rates as a function of θ_1, θ_2 and θ_3. The 3D space of θ_1, $\theta_2$and θ_3 has been divided into seven regions; they are presented in the Figure 2.. Also the sensitivity of the profit to the parameters can be identified. The profit is more sensitive to θ_1; in CR 5 to CR 7 it is not sensitive to θ_3 at all. Thus, for any value of θ_2 that lies in CR 3, the uncertainty in the availability of raw material 1 will not affect the profit. This type of information is useful for solving reactive or on-line optimization problems. Such problems usually require a repetitive solution of optimization problems so as to compute the actions that must be taken at regular time intervals. This requirement comes from variations, such as demand fluctuations, during plant operation and to optimally control the plant under such dynamic behaviour.

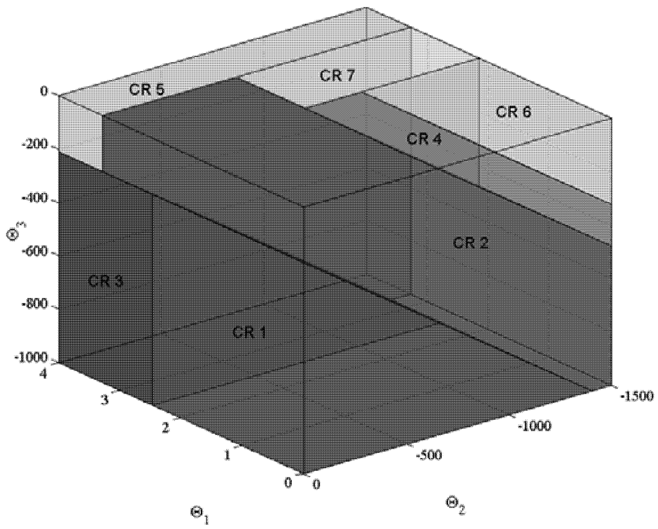

Figure 2 A 3D presentation of the parametric solution

Table 2 Parametric solution of the example case.

CR	Optimal solution	*CR*	Optimal solution
1	Profit(θ) = -40000θ_1 + 2.47θ_2 + 8.73θ_3 + 194793 x_1 = 1.43 θ_2 – 1.43θ_3 + 13857, x_2 = -0.43θ_2 + 1.43θ_3 + 11143 x_3 = 0.43θ_2 – 0.43θ_3 + 3957 x_4 = -0.43θ_2 + 1.43θ_3 + 11043	4 5	Profit(θ) = 40000θ_1 + 6.2θ_2 + 2.2θ_3 + 194061 x_1 = 0.4 θ_2 + 0.4θ_3 + 13857, x_2 = 0.6θ_2 - 0.4θ_3 + 11240 x_3 = 0.12θ_2 +0.12θ_3 + 4328, x_4 = -0.12θ_2 + 0.88θ_3 + 10672 Profit(θ) = 397906θ_1 + 7.28θ_2 + 192965 x_1 = 0.63θ_3 + 14156, x_2 = 0.38θ_3 + 10843
2	Profit(θ) = -40000θ_1 + 5.53$_2$ + 3.28θ_3 + 193652 x_1 = 0.87θ_2 – 0.43θ_3 + 14065 x_2 = 0.13θ_2 + 0.43θ_3 + 10934 x_3 = -0.13θ_2 + 0.56θ_3 + 4165 x_4 = 0.13θ_2 + 0.43θ_3 + 10834	 6	x_3 = 0.19θ_3 + 4047, x_4 = 0.38θ_3 + 10743 Profit(θ) = 40521θ_1 + 7.38θ_2 + 195191 x_1 = 0.63θ_3 + 13969, x_2 = 0.38θ_3 + 11031 x_3 = 0.19θ_3 + 4391, x_4 = 0.38θ_3 + 11131
3	Profit(θ) = - 40372θ_1 + 13.1θ_3 + 195713 x_1 = 1.1θ_3 + 14389, x_2 = 0.67θ_3 + 10983 x_3 = 0.33θ_3 + 4117, x_4 = 0.67θ_3 + 10883	7	Profit(θ) = 40366θ_1 + 7.38θ_2 + 194853 x_1 = 0.63θ_3 + 13906, x_2 = 0.38θ_3 + 11094 x_3 = 0.19θ_3 + 4372, x_4 = 0.38θ_3 + 10994

In the dynamic case the parameters θ_1, $\theta_2$and θ_3 are time dependent. Figure 3. (left) presents the time series. The profitability is studied as a function of state-transition cost Q:

$$\min_{\{u(t)\}_{t_0}^{t_0+T}} \int_{t_0}^{t_0+T} dt\left[\frac{dx^T}{dt}Q\frac{dx}{dt}+f_{static}(x,\theta(t))\right] \tag{3}$$

$$s.t. \quad g_{static}^{(n)}(x,\theta(t)) \le 0$$

The problem is solved with dynamic programming with respect to the inequality constraints g_{static} defined by the static case. The variables x_1 ... x_4 that describe the raw material flows change now as a function of $\theta(t)$ and Q. Q is the same for all variables. Increasing the state-transition cost forces the optimization algorithm to search solutions with less dramatic control actions. Figure 3. (middle) presents examples of the variable x_1 as a function of Q. In order to minimize the overall cost the optimization must balance between the profitability and the state-transition cost. Figure 3. (right) presents the profit as a function of Q. The profit decreases fast as the state-transition cost increases.

Allthough the static example case provides parametric solution to the problem, the addition of state-transition cost makes the control actions more realistic. The parametric solution may suggest too radical changes to the process. Obviously this is case dependent and the selection of parameters is difficult. The results from the example case presented here are merely suggestive. However, they indicate that the presented methodology can be applied to optimize the production of the integrated biorefinery processes, since the problems that arise can be modeled in the similar manner as the example case – multiple raw materials are processed in sub processes creating a selection of sub products and end products.

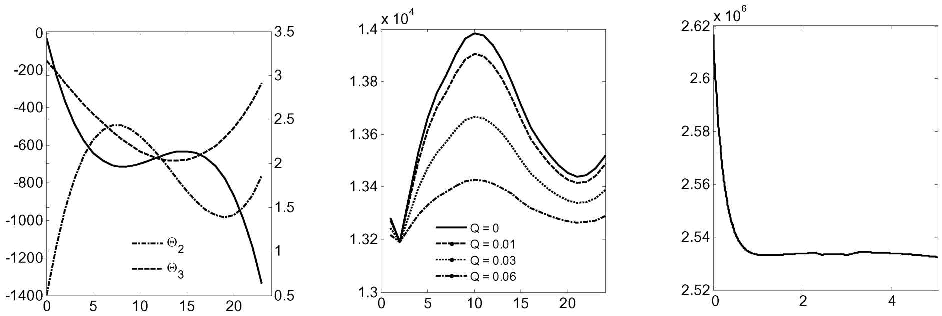

Figure 3 Left: Time seris of the parameters θ_1, $\theta_2$and θ_3. Right y-axis is for θ_1
Middle: Variable x_1 as a function of state-transition cost Q.
Right: Profit as a function of state-transition cost Q.

Conclusions

The need to maximize the production of main and side products as well as power production is in the background of the development of biorefineries. There are many alternatives how to execute the biorefinery concept. When the biorefineries are brought from the conseptual level to reality, proper methods for the optimal production plannig are needed. These methods should consider flexibility of production, uncertainties of supply, demand and prices of raw-materials and products as well as variable costs of production.

The studies with the example case show that the combination of parametric and dynamic programming can be utilized in the optimized scheduling of integrated biorefineries. The problems that arise can be modeled in the similar manner as the example case – multiple raw materials are processed in sub processes creating sub products and end products.

References

Acevedo, J., Pistikopoulos, E.N., 1997, A multi-parametric programming approach for linear process engineering problems under uncertainty, Ind Eng Chem Res.

Acevedo, J., Pistikopoulos, E.N., 1999, An algorithm for multi-parametric mixed-integer linear programming problems, Operations Research Letters, Volume 24, Issue 3, Pages 139-148.

Acevedo, J., Salgueiro, M., 2003, An efficient algorithm for convex multi-parametric nonlinear programming problems, Ind Eng Chem Res.

Bemporad, A., Morari, M., Dua, V., Pistikopoulos, E.N., 2002, The explicit linear quadratic regulator for constrained systems, Automatica, 38:3–20.

Borrelli, E., Bemporad, A., Morari, M., 2003, A geometric algorithm for multi-parametric linear programming, J Optim Theory Appl..

Dua, V., Pistikopoulos, E.N., 1999, Algorithms for the solution of multiparametric mixed-integer nonlinear optimization problems, Ind Eng Chem Res, 38:3976–3987.

Dua, V., Bozinis, NA., Pistikopoulos, E.N., 2002, A multiparametric programming approach for mixed-integer quadratic engineering problems, Comp Chem Eng, 26:715–733.

Li, Z., Ierapetritou, M.G., 2007, Process scheduling under uncertainty using multiparametric programming, AIChE J., 53 , 3183.

Pistikopoulos, E.N., Georgiadis, M.C., Dua, V., 2007a, Multiparametric Programming, Process Systems Engineering, Vol. 1, Weinheim, Germany: Wiley-VCH.

Pistikopoulos, E.N., Georgiadis, M.C., Dua, V., 2007b, Multiparametric Model-Based Control, Process Systems Engineering, Vol. 2. Weinheim, Germany: Wiley-VCH.