A model predictive control framework for advanced planning and scheduling in process industries

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Abstract- This paper presents a model predictive control (MPC) formulation for the planning and scheduling problem in process industries. The main idea is to use a moving horizon technique as well as a feedback control concept to continuously update production schedules and plans. In existing planning and scheduling formulations, a mixed integer (non)linear programming is very often solved over a chosen horizon which depends on the level of granularity considered. To account for new orders or plant disturbances such as equipment failures or some parameters deviations (production yields, rates or state deviation affecting the production quality), updated production schedule and plan are needed. In this paper, the process of rescheduling (replanning) is compared to a classical feedback control where the result of current schedule which is the inventory and/or desired profit.

I Introduction

Due to the growing demand on product quality and range and the desire to maximize profits, companies have diversified their product portfolio and developed multi-product plants. Besides, recent consolidation of industrial activities has brought together production facilities and reinforced the need for an advanced management. To use and exploit better relevant plant information, the decision making process needs to model the plant operation and use an optimization procedure exploiting this model.

The difference between planning and scheduling depends on the level of details and time horizon considered. In a typical planning process, one wants to determine the volumes of products to be produced so as to make a maximum profit. In effect, based on demand forecast, confirmed orders and new product request, a planning exercise consists of deciding on quantities of products at different subperiods of the time horizon when intermediate deliveries are considered. So doing, the planning period is divided into block intervals, each block corresponding to the production of a group of product grades or customer orders. Here the objective is to determine whether the production is profitable or not. The details on equipment capacities, production constraints and recipe rules are considered in the scheduling task where the goal is to find the right sequence of grade production within the time horizon, so as to reduce production cost and/or production lead-time.

Several modelling framework including a continuous model representation and a discrete-time representation have been proposed to represent plant operation. The so-called resource task network (RTN) is a discrete-time formulation contains both material balances and scheduling formulation [6, 7]. In this formulation, the scheduling horizon is divided into time intervals of equal length. In the case where a long horizon compared to the time intervals is considered, this results in a very large problem which increases the optimization complexity. Another formulation which has less integer variables is the continuous-time formulation [9]. It provides a model for task assignment and sequencing. In [7], the authors proposed a model combining both discrete-time representation with material balance and continuous-time representation for sequencing and assignment. This approach allows to deal with the case where intermediate due dates within the horizon are considered.

In this paper, we propose to formulate planning and scheduling problems corresponding to the description above as a model predictive control framework. The motivation comes from the fact that when frequent changes occur, previous schedules are modified in the following horizon by adjustment. These adjustments may consist of changing the amount of processes materials and/or assignment and sequences. Recent related works are on mixed logic dynamic systems [3] and are considered in this paper in combination with other contributions.

Recent works [2, 8, 11] have proposed a study on the use of a dynamic approach for supply chain management. In these articles, the authors propose to use dynamic models and to use control laws to optimize variables such as customer satisfaction and inventory. The similarity comes from the fact that in each period, a forecasting tool (if available) provides possible demand in future periods in relation with market trends and past demand. Using this information, the planning task consists of matching this demand to production capacities by determining volumes of production (orders requests), and as a result desired inventory profiles. This task makes sure that the production is profitable. The scheduling task consists of reducing the cost of production so as to obtain the profit calculated by the planning. At this level, production capacity, sequencing constraints, operation rules (cleaning, setup times) need to be modelled.

The contribution of this paper is to use dynamic models of plant operation provided by a framework such as the RTN, to propose a model predictive planning and scheduling. Related works are also in [8, 11] In this formulation, an initial trajectory generation for inventory profiles within a horizon is used as input to the dynamic planning and scheduling. This profile is recalculated whenever a new order arrives or a capacity reduction occurs. Next, a quadratic objective function is used to ensure disturbance rejection (such as failure, or yield and efficiency variations). The resulting formulation is a MIQP problem. The main advantage of the formulation is the reduction of the combinatorial complexity by small modification of the schedule and plan.

This paper is organized as follows. In section 2, the formulation of the predictive planning and scheduling is proposed. Some comparisons with current practice are provided. In section 3, an illustrative example is proposed and some discussions on the applicability of such framework is propose. The article ends with some open issues and perspectives.

II Planning and scheduling in the process industries

This subsection presents how existing modelling frameworks can be used to derive a straightforward state space model for a model predictive approach to planning and scheduling. Later, optimization aspects are discussed.

A Modelling

To illustrate the development in this paper, consider a simplified example (Figure 1) representing a two stage process. This could be only a part of a larger plant, chosen here for sake of clarity of the presentation.

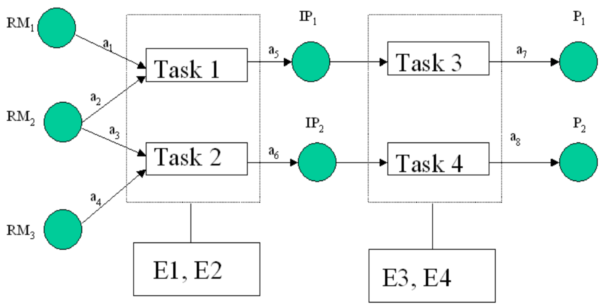

Figure 1: Simplified example

In this example, E_1, E_2, E_3 and E_4 represent equipments which are used for processing at the corresponding stages. $RM_s,\ \ s = 1, 2, 3$ are raw materials, $IP_1,\ IP_2$ are intermediates and P_1, P_2 are the resulting products. The following matrix summarizes the mapping of units to tasks and variables.

Units	Tasks	Integer variables	constraints
E_1	T_1, T_2	$i_{11}(k), i_{21}(k)$	$i_{11}(k) + i_{21}(k) \leq 1$
E_2	T_2	$i_{22}(k)$	
E_3	T_4	$i_{33}(k)$	
E_4	T_3, T_4	$i_{34}(k), i_{44}(k)$	$i_{11}(k) + i_{21}(k) \leq 1$

Table 1: Unit and task mapping

$i_{ij}(k) = 1$ if task T_i is performed with equipment E_j at time instant k, $i_{ij}(k) = 0$ otherwise. Writing the mass balance of the two stages leads to:

$$\begin{cases} IP_1(k+1) = IP_1(k) + a_5(a_1 RM_1(k) + a_2 RM_2(k))i_{11}(k) \\ IP_2(k+1) = \\ IP_2(k) + a_6(a_3 RM_2(k) + a_4 RM_3(k))(i_{21}(k) + i_{22}(k)) \\ P_1(k+1) = P_1(k) + a_7 IP_1(k)(i_{33}(k) + i_{34}(k)) \\ P_2(k+1) = P_2(k) + a_8 IP_2(k) i_{44}(k) \end{cases}$$

where IP stands for Intermediate product, P for product, y is for measurement, RM for raw material. The a's are the proportion of streams used for to each task. When no proportion is specified, it is assumed to be 1. In addition to these constraints, one should add capacity limitation of storage.

$$RM_{ms} \leq RM_s \leq RM_{Ms} \tag{1}$$
$$IP_{ms} \leq IP_s \leq IP_{Ms} \tag{2}$$
$$P_{ms} \leq P_s \leq P_{Ms} \tag{3}$$
$$\tag{4}$$

As suggested in the literature, minimum production runs are considered, for say for T_1, as:

$$i_{11}(k) = \ldots = i_{11}(k+1) = \ldots = i_{11}(k+T_1) \tag{5}$$

where $T_1 \Delta t$ is the minimum run length of T_1, Δt is the time interval of discretization. The measured outputs are the products inventory levels. More generally, State Task modelling leads to a bilinear system of the following form:

$$\begin{cases} x(k+1) = A_0 x(k) + B_0 u(k) + \\ \sum_{s=1}^{m} i_s(k)(A_s x(k) + B_s u(k)) \\ y(k) = Cx(k) \\ x(0) = x_0 \end{cases} \tag{6}$$

where x and u are respectively the state (inventory of storage facilities, raw material consumption terms etc.) and the input (raw material) variables, y is the measured output which corresponds to inventory. i_s represent a binary variable associated to the decision to assign certain tasks to certain equipments at a given time k. Matrices A_j contain proportions of feeds to a task and proportions of resulting products.

To account for equipment constraints and operation rules, a linear constraint can be derived (this may be a nonlinear constraint):

$$Ex(k) + Fi(k) + Gu(k) \leq Q \tag{7}$$

Additional equations can be added to account for the time dependent binary variables (e.g. in the case of cleaning of vessel, the task of clean will depend upon the previous task). The same could be applied to the case where a maintenance task would be performed after a certain number of operations.

However, this modelling approach induces a large number of integer variables. To reduce their number, a time aggregation technique can be used. Another modelling approach is to use a continuous-time [9] approach which deals mostly with task assignment and sequencing. When the focus is on tracking material and taking into account capacity produced inside the plant, this model needs to be complemented with a material balance as in [7]. It also allows to account for intermediate due dates of orders.

B Optimization

Due to the presence of the binary variables, the problem becomes bilinear and the objective function is nonconvex. To overcome this difficulty, auxiliary variables $B_{sj}(k) = x_s(k)i_j$ are linearized as follows: $x_{m_s} i_j(k) \leq B_{sj}(k) \leq X_{M_s} i_j(k)$ where x_{m_s} and X_{M_s} are the lower and the upper bounds of x_s.

In the present approach, it is proposed to use a continuous formulation for sequencing and assignment. The result is a determination of the integer variable in the mass balance as in [7].

The need for a "predictive-like" formulation for planning and scheduling arises from the fact that yields (the a_is), raw material and product prices may vary. Also, failures on units may result to presetting the values of some of the binary variables, thus modifying initial setup in plan and schedule. In this configuration, only the first few scheduled tasks will be applied. The rest may not be applied if a change or disturbance occurs. Also, a yield or rate estimation should be triggered to update schedule and plan. In the following section, the formulation of planning and scheduling is revisited to derive an applicable control concept.

III A MPC framework for planning and scheduling

The discrete-time model leads to a hybrid system in the form of mixed logic dynamic system [3]. A Mixed Integer Quadratic Programming optimization has been used recently for the optimization of mixed logic dynamic systems [3]. In this paper, we show how such an approach fit in an overall Solution to manufacturing operation planning and scheduling.

A trajectory generation

In most industry application (refinery, petrochemicals, pulp and paper), a long-term planning system is used to determine which products to make and how much (mostly for a month to a year). This exercise consists of finding if the current production requirements are within the operability of the plant. If so, the task is find a feasible plan and acceptance of orders. This results in inventory target generation for each product as shown in figure (2). Most of current approaches contribute to off-line trajectory optimization. Very often, the some tools are used to modify the targets when new orders are requested. Assuming that derived trajectory is satisfactory and feasible (if not optimal), the next step is to make sure that in the execution, one will always be closer to this targets.

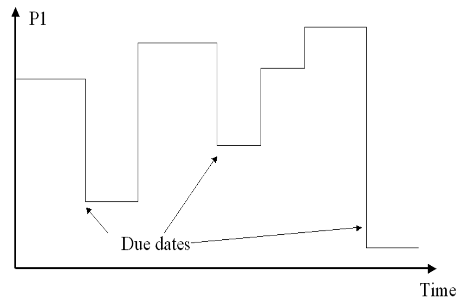

Figure 2: Required trajectories

During the execution of derived plan and schedule, one wants to minimize deviations to the calculated target for:

- Realizing the profit calculated at the planning level.
- Fulfilling due date commitment when possible or alternatively reduce penalty cost.

The time horizon used for the execution is shorter that the planning level. A moving horizon is also considered.

B Implementation

As described in the previous section, one wants to minimize the following objective function:

$$J_T = \sum_{i=k}^{k+N} (y(k) - y_r(k))^T Q (y(k) - y_r(k)) + \quad (8)$$
$$(u(k) - u_r(k))^T R (u(k) - u_r(k)) + \Delta u(k)^T P \Delta u(k)$$

Where y_r is the desired profile of inventory, u_r the corresponding raw material quantities or others inputs such as energy. u_r and y_r are determined through target generation. The matrices Q and R should contain penalty terms of penalties due to these deviations. For applying a predictive control strategy, a state space model (6) is used. However, the linearization presented in the previous section is not directly be used. Instead, the error dynamics are considered:

$$e(k+1) = A_0 e(k) - B_0 \delta u(k) + \sum_{s=1}^{m} i_s(k)(A_s e(k) + B_s \delta u(k)) \quad (9)$$
$$+ \sum_{s=1}^{m} (i_s(k) - i_{rs}(k))(A_s x_r(k) + B_s u_r(k))$$

where $\delta u(k) = u(k) - u_r$. In the above equation, assuming that the state deviation e are known (measurement of tank levels or warehouse stocks), the problem is reduced to finding the inputs deviations $\delta u(k)$ and integers $i_s(k)$ so as to minimize the cost function. Determining $\delta u(k)$ means finding which variation to the current throughput should be considered to correct the deviation. As this might not be sufficient, changes in sequences and assignments of operation are also considered. This approach has the merit to reduce the number of variables dealt with. The linearization presented in the previous section can also be applied to this error based equation.

Moreover, certain integer variables can be fixed to allow finishing on started tasks, or for some important tasks to come (maintenance, important customer orders etc.). In that case constraint such as (5) may be used where T_1 would be minimum time remaining to finish the task.

Another issue in executing a plan or predetermined schedule is that recipe coefficients in matrices A_j vary to to feedstock quality or equipment performance. A real-time yield calculation and data reconciliation tool can be used to update and maintain the model. This can also result in a change in execution to catch up the eventual delays.

Here, there should be a safety margin to ensure that stock will allow dealing with uncertainties such as equipment breaks or poison in reactor etc. This should be generated by a stochastic tool (this is not covered in this paper). Also, it is assumed that the trajectory generator exists (This could be from an overall planning system which makes sure that order taken are profitable) and that the due dates and quantities of products per orders are already determined.

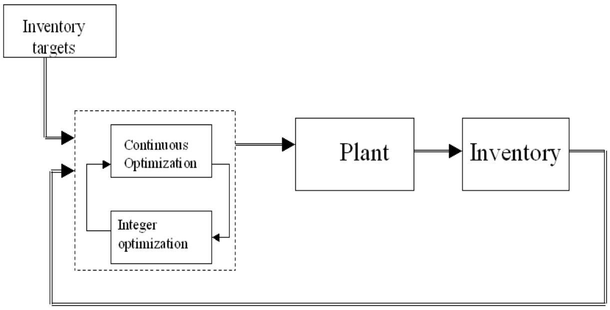

Figure 3: Control structure

IV Conclusion and future investigations

In this paper, the propose approach deals with the execution of precalculated plans and schedules. It is proposed a model predictive scheme to optimize deviations from targets provided by off-line planning and scheduling. The proposed method has potential of providing faster solution by solving a reduced problem, the complete one being solved off-line and taking into account more complex parameters (economic, tactical, strategic issues). The proposed approach provides a real time measurement of deviations of profits and some corrections to realize initially planned production. Issues such as continuous switching avoidance and study of full operability of plant (real time plant availability calculation) are not considered in this paper.

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