An Investigation to Manufacturing Analytical Services Composition Using the Analytical Target Cascading Method

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Kai-wen Tien[1] and Boonserm Kulvatunyou[2] and Kiwook Jung[2] and Vittaldas Prabhu[1]

[1] Penn State University, State College, U.S.A.
{kut147,vxp7}@engr.psu.edu
[2] National Institute of Standards and Technology, Gaithersburg, U.S.A
{serm,kiwook.jung}@nist.gov

Abstract. As cloud computing is increasingly adopted, the trend is to offer software functions as modular services and compose them into larger, more meaningful ones. The trend is attractive to analytical problems in the manufacturing system design and performance improvement domain because 1) finding a global optimization for the system is a complex problem; and 2) sub-problems are typically compartmentalized by the organizational structure. However, solving sub-problems by independent services can result in a sub-optimal solution at the system level. This paper investigates the technique called Analytical Target Cascading (ATC) to coordinate the optimization of loosely-coupled sub-problems, each may be modularly formulated by differing departments and be solved by modular analytical services. The result demonstrates that ATC is a promising method in that it offers system-level optimal solutions that can scale up by exploiting distributed and modular executions while allowing easier management of the problem formulation.

Keywords: Factory design and improvement · Integration optimization · Analytical target cascading · Smart manufacturing · Services composition

1 Introduction

As cloud computing is increasingly adopted, the trend is to offer software functions, including analytical software functions, as modular services and compose them into larger, more meaningful ones [1,2]. The trend is attractive to analytical problems in the manufacturing system design and performance improvement domain because 1) finding a global optimization for the system is a complex problem; and 2) sub-problems are typically compartmentalized by the organizational structure. However, solving sub-problems independently can result in a sub-optimal solution at the system level. This paper investigates the technique called Analytical Target Cascading (ATC) to coordinate the optimization of loosely-coupled sub-problems. Each sub-problem may be independently formulated by each stake-holding organization and be solved by modular analytical software services.

This study is motivated by the Factory Design and Improvement reference activity model developed in [3]. The model decomposes major activities into subtasks and key decision-makings needed in a typical factory design and performance improvement project. It entails the needs for interactions across optimization problems at multiple control-levels.

For simplification of the illustration, this paper investigated the ability of ATC to coordinate three sub-problems at the manufacturing process control level including capacity design, lot sizing, and storage layout design. These three sub-problems are interlinked and typically dealt by different stakeholders. Their linkages are shown in Fig. 1.

Many analytical techniques have been developed to solve each of these three sub-problems. These techniques are often used in isolation, but these problems are not independent. A change in one formulation can influence the outcomes and feasibilities of the other two. Therefore, capturing those dependencies and using them to integrate these three sub-problems is crucial.

ATC has been used to solve multidisciplinary-design-optimization problems that comprise heterogeneous sub-problems. These sub-problems are solved separately; but, each of their interim solutions is communicated regularly. This not only speeds convergence, it also gives a better solution than the one that is generated with no communication or one-way communication (such as in the hierarchical model in Fig. 1). The algorithm that ATC uses has been studied extensively and its convergence properties have been established mathematically [4]. The primary application of ATC has been in designing complex products such as automobiles and aircrafts [5,6]. Nevertheless, it has also been used in integrating supply chains and integrating marketing and production (DFM) [7,8].

The result of this investigation indicates that ATC is a promising method in that it offers (1) easier management of the problem formulation of the overall system and (2) coherent, optimal solutions that can scale up to the size of the overall system by exploiting distributed and modular executions.

The rest of the paper is organized as follow. In Section 2, the analytical sub-problems are introduced; and it discusses drawbacks of the two traditional integration structures to compose these sub-problems: centralized and hierarchical. Then, the mathematical formulation of the proposed ATC-based collaborative structure illustrated in Fig. 1(c), is described in Section 3. In Section 4, we apply ATC to the sub-problems and analyze the results using data from a production project at Penn State [9]. Finally, the conclusion is presented in Section 5.

2 Composing Manufacturing Analytical Models

In this section, we introduce the three optimization sub-problems and their corresponding links. The exact links depend on the multi-criteria optimization of throughput (TH), inventory (INV), and work-in-process (WIP). Links can be seen as either common decision variables or input/output parameters, which are assumed to be non-negative.

Note: $\pi(\cdot)$ is a penalty function which is used in the collaborative model and will be explained in section 3.1. In this section, we set it as a zero function.

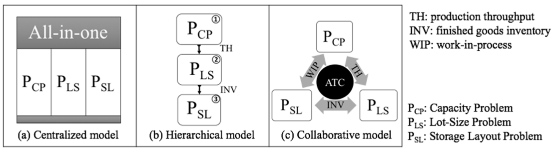

Fig. 1. Search methodology

2.1 Capacity Optimization

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$$(P_{CP}) \qquad \min\ z_1(\mathrm{TH},\ \mathrm{WIP}) = c_w \cdot \mathrm{WIP} + \pi(\mathrm{TH},\ \mathrm{WIP})$$

$$s.t. \quad \mathrm{CT_q} = \frac{c_a^2 + c_e^2}{2} \cdot \frac{u}{1-u} \cdot t_e \tag{1}$$

$$\mathrm{WIP} = \mathrm{TH} \cdot \mathrm{CT_q} \tag{2}$$

$$u = \mathrm{TH} \cdot t_e \tag{3}$$

$$TH \le \mathrm{TH_{limit}} \tag{4}$$

Where c_w is the unit cost for holding one unit of WIP during the planning period, and π represents any penalty functions. Equation (1) represents the approximation of the waiting time in queue, CTq, in a G/G/1 system. The formulation shows that $\mathrm{CT_q}$ is effected by the coefficient of variation (CV) of inter-arrival times c_a, the CV of effective processing times c_e, the utilization u, and the effective process time t_e. The formulation can be generalized to multi-machine, multi-station systems. (2) represents the Little's law formula. (3) shows the equation of utilization and (4) restricts TH.

2.2 Lot-Sizing Optimization

A wealth of models can be used for making lot-size decisions including EOQ (Economic Order Quantity) and EPL (Economic Production Lots) [10]. Here, we minimize the total inventory cost over T periods.

$$(P_{LS}) \qquad \min\ z_2(\mathrm{TH},\ \mathrm{INV}) = \sum_{t=1}^{T} p_t x_t + h_t i_t + \pi(\mathrm{TH},\ \mathrm{INV})$$

$$s.t. \quad i_t = x_t + i_{t-1} - D_t, \quad \forall t = 1 \ldots T \tag{5}$$

$$x_t \le \mathrm{TH{\cdot}WH}, \qquad \forall t = 1 \ldots T \tag{6}$$

$$x_t + i_{t-1} \le \mathrm{INV}, \qquad \forall t = 1 \ldots T \tag{7}$$

Where p_t is the unit production cost and h_t is the unit holding cost for period t. Equation (5) shows the inventory balance in each period, in which D_t is the demand and x_t is the production amount in period t. The constraint (6) indicates the production amount should be less than capacity limit, in which WH is the available working hours during the period. Equation (7) shows the inventory level should be less than INV.

2.3 Storage Layout Optimization

The storage layout sub-problem determines the optimal layout to minimize the material handling costs in terms of the distances 1) from WIP storage locations to locations of machines, and 2) between finished-goods inventory locations to the shipping docks. The storage layout problem is usually formulated as an assignment problem in which the storage floor is first subdivided into N grid squares and each item (WIP or INV) is assigned to a grid square.

$$(P_{SL}) \quad \min \ z_3(\text{INV},\ \text{WIP}) = \sum_{k=1}^{N} [c_k^{(w)} y_k^{(w)} + c_k^{(f)} y_k^{(f)}] + \pi(\text{INV},\ \text{WIP})$$

$$s.t. \sum_{k=1}^{N} y_k^{(w)} \geq \text{WIP} \tag{8}$$

$$\sum_{k=1}^{N} y_k^{(f)} \geq \text{INV} \tag{9}$$

$$\mathrm{y}_{\mathrm{j}}^{(w)} + y_j^{(f)} \leq 1, \qquad \forall\ j = 1, 2,\ \ldots,\ N \tag{10}$$

$$y_k^{(w)},\ y_k^{(f)} \in \{0,\ 1\} \tag{11}$$

Where $c_k^{(w)}$ and $c_k^{(f)}$ are the material handling cost for respectively storing one work-in-process and inventory in the grid square k. $y_k^{(w)}$ ($y_k^{(f)}$) is a binary decision variable, which value is 1 if one unit of WIP (INV) is assigned to the grid square k. (8) and (9) represent the storage spaces demanded for WIP and INV, respectively. (10) restricts that one grid square can store only one unit of the items.

2.4 Centralized vs. Hierarchical Integration Structures

The centralized-structure approach, shown as Fig. 1(a), is an intuitive and coherent way to think about integrating the sub-problems. It results from minimizing the three objective functions of the sub-problems subject to all constraints (1) to (9). So, in essence there is only one, multi-objective function and one set of constraints. There are, however, two serious drawbacks associated with this centralized approach. First, is the issue of poor scalability of the approach in terms of the increasing number of decision variables and constraints. The other drawback occurs when reformulation of the model is needed, e.g., when the factory changes: essentially you basically have to start over.

The hierarchical-structure approach, shown in Fig. 1(b), reduces, but does not eliminate, the difficulty in addressing these two challenges. The sub-problems are solved individually, so reformulation is easier. Additionally, the sub-problems are typically solved in a prescribed order. That order is P_{CP}, P_{LS}, then P_{SL}[4]. The links are directed links and are obtained as the outputs of the previously solved sub-problems. Clearly, this approach is not guaranteed to find a coherent, optimal solution. In addition, the quality of the final solution is highly dependent on the initial inputs to the initial process, P_{CP}. Therefore, in practice, it requires many experiments, by varying the input conditions until an optimal solution is found across all the sub-problems!

3 Proposed Collaborative Approach

Our collaborative approach achieves both the high solution quality of the centralized approach as well as the reconfigurability of the hierarchical approach. The ATC algorithm connects sub-problems as if they were building-blocks. First, sub-problems at two ends of a link are assigned two specific roles: sender or receiver. Then, the link value in each sub-problem is replaced by two variables: target t_i and response r_i. The sender solves the target t_i and the receiver solves the response variable r_i within its own local variables and constraints. The ATC algorithm seeks to minimize the discrepancies between targets and responses with respect to the links. In this paper, as we said above, P_{CP} is the sender of both WIP and TH; P_{LS} is the receiver of TH and the sender of INV; and P_{SL} is the receiver of both WIP and INV as Fig. 1(c).

3.1 The Collaboration strategy

In order to achieve global consistency, each of the three sub-problems is assigned a different penalty function. It “punishes” a sub-problem, by adding high costs to its objective function, when its solution violates consistency constraints. Realizing this, we decided to use the augmented Lagrangian as our penalty function and the basis for our collaboration strategy [11]. The penalty function is shown in equation (12). Note that the notation “∘” means the elementwise product for arrays.

$$\pi(\cdot) = \sum_{i=1}^{n_t} (v_i t_i + \|w_i \circ (t_i - \overline{r_i})\|_2^2) + \sum_{j=1}^{n_r} (-v_j r_j + \left\| w_j \circ \left(\overline{t_j} - r_j\right) \right\|_2^2) \tag{12}$$

The Lagrangian penalty function includes two new variables, Lagrangian multiplier v_i and quadratic penalty weight w_i. They are updated in the outer loop of ATC. The updating methods are expressed below, where l represents the iteration of the ATC algorithm.

$$v_i\,(l+1) = v_i\,(l) + w_i(l) \circ w_i(l) \circ (t_i(l) - r_i(l)) \tag{13}$$

$$w_i\,(l+1) = \beta\ \circ w_i(l) \tag{14}$$

The ATC algorithm has three main steps:

Step 1: Inner loop – solving sub-problems separately and updating the target and response variables.
Step 2: Outer loop – updating the Lagrangian multipliers and weights via expression (13) and (14).
Step 3: Termination – terminating the algorithm when the discrepancies of all target and response pairs are smaller than a given tolerance.

3.2 Reconfigurability and Discrepancy Visualization

As mentioned in the previous section, the ATC algorithm connects the sub-problems through target and response variables. It has the advantage of reusability. Suppose, for instance, a company wants to replace their current EOQ sub-problem with a (Q, r) sub-problem for lot-sizing design; the other two sub-problems are still reusable. Furthermore, since the overall system-problem has been partitioned into three sub-problems, the structural complexity of the overall system is reduced. Stakeholders of each sub-problem can also formulate their problems independently; therefore, the factory design and performance improve project can progress efficiently.
The ATC approach also allows feasibility issues across sub-problems to be conveniently resolved. It monitors the target/response values and showing the discrepancies between differing objectives in sub-models. For example, if there was a space reduction made in P_{SL} problem causing the responses r_{WIP} and r_{INV} not meeting the targets given by the other two sub-problems. The discrepancy can be shown in the results. This allows for the stakeholders to effectively collaborate and resolve the specific conflict.

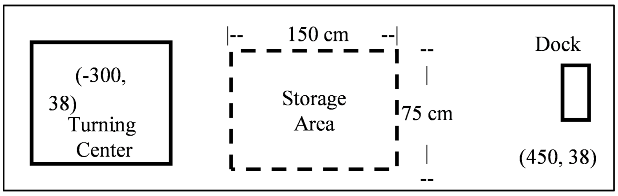


Fig. 2. Factory layout

4 Case Study

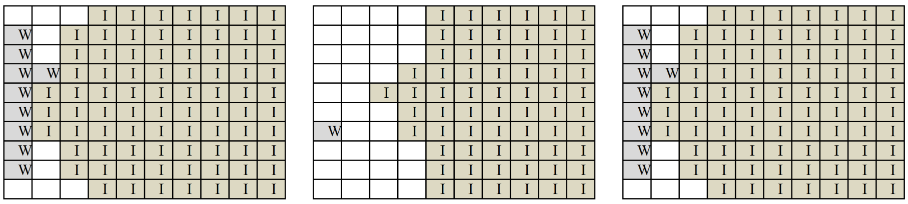
We use the IME Inc. project [9] to demonstrate the potential benefits of our collaborative approach over the other two. The aluminum chess set is the primary product in this case study. The associated process plan includes only one turning center and 240 labor hours. In addition, the product will be delivered to customers at the end of each quarter (March 31th, June 30th, etc.). Note, this knowledge could be used to determine the minimum value for storage size. That minimum value has to be large enough to store both WIPs and finished products during that time. Table 1 shows the parameters for the design sub-problems. c_a is approximated by the variance of the demand and c_e is significant because of the long set-up time of this product. t_e represents the effective processing time for the whole chess set. The production costs p_t changes because of the fluctuation of material costs. The holding cost for one set per one week is estimated by the typical interest rate per quarter (about 6.25%) times the production costs. The factory has 150×75 (cm^2) area for both WIP and the finished products (see Fig. 2). A finished product is wrapped into a 15×7.5×7.5 (cm^3) box. Moreover, the boxes cannot be piled up because of the strength of the boxes. Hence, the storage area is divided into a grid of 100 squares, each of which can store only one box or one working-in-process. The material handling cost of a finished product at a certain location is calculated by multiplying the unit operation cost with the rectangular distance between the machine and the exit dock. With a technician's suggestion, we assume the unit costs of the material handling costs is $0.01/2.5 centimeter.

Table 1. The parameters of sub-problems

$\mathbf{P}_{CP}$ **Sub-problem**		$\mathbf{P}_{LS}$ **Sub-problem (Quarterly Plan)**		$\mathbf{P}_{SL}$ **Sub-problem**	
c_a	0.685	p_t($/sets)	(20.0, 25.0, 18.0, 20.0)	Area (cm^2)	(150, 75)
c_e	0.942	h_t($/sets)	(1.25, 1.56, 1.13, 1.25)	Box (cm^2)	(15, 7.5)
t_e(hrs)	1.388	D_t(sets)	(100, 80, 130, 90)	Unit cost ($/cm)	0.01
c_w($)	4	WH(hrs)	240		

Table 2. The computational results

	Centralized model	**Hierarchical model**	**Collaborative model**
Comp Time (sec)	4.9176	0.0742	132.7390
Total Cost ($)	8290.5	8388.4	8290.5
(TH_0, WIP_0, INV_0)	(0.43, 0, 0)	(0.43, 0, 0)	(0.43, 0, 0)
(TH*, WIP*, INV*)	(0.67,7.80,80.01)	(0.43,0.54,62.5)	(0.67,7.80,80.01)



(a) Centralized model (b) Hierarchical model (c) Collaborative model

Fig. 3. The storage layouts

The desired throughput (initial value) is determined by the average demand rate 0.43 sets/hr. The three models were constructed and run in MATLAB 2015a. The collaborative model was terminated after 96 iterations, resulting in a tolerance value of 10E-6 for the discrepancies between sub-problems. When terminated, w = (1, 1, 1) and v = (-3.75, 1.34, 1.76). The results show that the proposed collaborative approach can find the same solution as overall optimal solution generated by the centralized approach, but the hierarchical approach cannot. However, the computation time of the collaborative model is much larger than those of the other two (less than 5 seconds). This implies that the collaborative model is more suitable for solving problems in the factory "design stage," where the system complexity issue is much more critical than the computational time. Nevertheless, a parallel computing model could be explored to speed up the solver to provide a solution in a near real-time.

5 Conclusion

In this paper, we proposed a collaborative approach, called Analytical Target Cascading (ATC), to composing analytical sub-problems and possibly associated software services to meet the overall objective. Our experiment shows a promising result. Sub-problems can be formulated and executed modularly and possibly under a distributed computing scheme. Even so, ATC connects these sub-problems and has the capability to achieve the coherent optimal as in the centralized model. Furthermore, unlike the centralized approach, our approach allows sub-problems to be changed or improved easily. Moreover, the discrepancies between targets and responses in each sub-problem are visible allowing for feasibility issues to be easily resolved. In the future work, we are planning to integrate control-level problems and design-level problems.
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