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# Simultaneous Dynamic Pricing and Manufacturing Scheduling

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## 1 Introduction

This paper focuses on simultaneous dynamic pricing and scheduling within a Manufacturing as a Service (MaaS) context. Scheduling-related work in MaaS includes [2], who investigate scheduling with tardiness optimization and eligibility scores. In [4], ontology-based matchmaking and scheduling for MaaS is described. An example of a scheduling setting for metal sheet manufacturing, that is solved with a genetic heuristic, is provided in [3]. In parallel, revenue management is frequently defined as the science of setting the right price for the right service at the right time for the right type of customer [5]. In [1], the authors consider pricing for MaaS platforms based on stylized models without the aspects of scheduling.

Many stylized revenue management settings model pricing and scheduling with queueing theory. For instance, [6] studies a stylized setting with pricing decisions by customers and wage decisions by agents, using queue theory to model job processing. In [7], the authors model collaborative job reassignments in additive manufacturing as a multistage combinatorial auction. Active revenue management implies the application of dynamic pricing, and standard techniques become less applicable in an industrial context due to the combinatorial nature of scheduling and the continuous nature of the dynamic pricing component, even from the viewpoint of an individual MaaS serving customer demand. In this work, we address this gap by jointly considering dynamic pricing and scheduling, relying on genetic heuristics, sampling, and integrated optimization.

## 2 Problem Statement

Let time periods  $t$  range from 1 to  $T$ , with the value-to-go function representing total expected revenue from period  $t$  onward, denoted by  $J_t$ . There are  $N$  different **job types**, and we assume that the type of job includes job-specific features, e.g., requirements, complexity, materials, and due dates. Each **order** consists of up to  $D$  jobs of the same type. There are  $M$  machines, and for each job type, we know the set of machines that can perform this job type. The order describing the amount and type of jobs requested by a particular customer is revealed at the beginning of a time period. The order explicitly identifies the customer, and there is a single order per time period. Let  $q_{nd}$  represent the probability of getting the order with job types  $n$  requesting  $d$  items. We denote such an order  $[n, d]$ . After the order is revealed, the manufacturer suggests the price  $p_{tnd}$ . We assume that the price is selected from the finite set of  $K$  options  $\mathcal{P}_{nd} = \{p_{nd}^1, p_{nd}^2, \dots, p_{nd}^K\}$ . Although it feels more natural to allow a continuous price, the discrete net of prices is provided for computational tractability with genetic heuristics. After the price is selected, the customer's decision is based on comparing their willingness to pay,  $w_{tnd}$ , with the proposed price,  $p_{tnd}$ . Willingness to pay is the maximum amount a customer is willing to pay for the job. The manufacturer knows the distribution of the willingness to pay,  $w_{tnd} \sim W_{tnd}$ , but not the exact value of each customer.

The production state is described by a tuple  $O_t$  and  $A_t$ , where  $O_t$  represents the currently accepted jobs that are not scheduled yet, and  $A_t$  represents jobs that already have a fixed schedule (i.e., already allocated to a certain machine at a specified time, but not necessarily processed). The distinction

between  $O_t$  and  $A_t$  is necessary to support partial scheduling updates while maintaining the flexibility to apply the information received in subsequent time periods. We assume that the state is updated according to the scheduling function  $S_t$ , i.e., this function decides on the jobs that should get a fixed allocation schedule at the beginning of the next time period. In this statement, we treat the scheduling step as a black box, with the purpose of supporting any scheduling algorithm with a compatible interface. For particular implementations, we may specify the scheduling algorithm explicitly. If an order with  $d$  items of job type  $n$  is accepted, the next state is computed via:

$$(O_{t+1}, A_{t+1}) = S_t(O_t + [n, d], A_t),$$

whereas if the price is not accepted, the next state is

$$(O_{t+1}, A_{t+1}) = S_t(O_t, A_t).$$

We introduce the function  $V_t(O_t, A_t)$  that accounts for costs related to job execution and delivery from state  $(O_t, A_t)$  to  $(O_{t+1}, A_{t+1})$  between consecutive time periods. The corresponding value function is then expressed in the following way:

$$J_t(O_t, A_t) = \sum_{n=1}^N \sum_{d=1}^D q_{nd} \max_{p_{tnd} \in \mathcal{P}_{tnd}} \mathbb{E}_{w_{tnd} \sim W_{tnd}} \left\{ \mathbb{P}(w_{tnd} \geq p_{tnd}) \left( dp_{tnd} - V_t(O_t + [n, d], A_t) \right) \right. \\ \left. + J_{t+1}(S_t(O_t + [n, d], A_t)) + \mathbb{P}(w_{tnd} < p_{tnd}) \left( J_{t+1}(S_t(O_t, A_t)) - V_t(O_t, A_t) \right) \right\}.$$

In this equation, the order with  $d$  items of job type  $n$  is revealed with probability  $q_{nd}$ , where  $\sum_{n=1}^N \sum_{d=1}^D q_{nd} = 1$ . Later, the manufacturer decides on the price to charge, and according to a distribution  $W_{tnd}$ , the willingness to pay  $w_{tnd}$  is revealed. If the customer's willingness to pay is above the price charged, the order is accepted for production. In this case, price  $p_{tnd}$  is charged for each of the  $d$  jobs in the order, the costs of fixed allocation are deducted, and the state is updated according to the scheduling function  $S$ . Otherwise, the order is not accepted, and the state of production is updated accordingly. Numerical experiments are in progress, and the corresponding results will be discussed during the conference.

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