Machine Learning Based Approximations for Some Production Control Problems with Product Returns and Remanufacturing

Arash GANDOMKAR GHALHAR, Bijan BIBAK, Fikri KARAESMEN,
Dept. of Industrial Engineering, Koç University, Sariyer, Istanbul, Turkey aghalhar22@ku.edu.tr , bbibak20@ku.edu.tr, fkaraesmen@ku.edu.tr,

Oktay KARABAG
Dept. of Industrial Engineering, Izmir University of Economics, Balçova, Izmir, Turkey oktay.karabag@ieu.edu.tr

Barış TAN
Dept. of Industrial Engineering, Özyegin University, Çekmeköy, Istanbul, Turkey baris.tan@ozyegin.edu.tr

Flow control for manufacturing systems with return loops of recycled products that can be refurbished or remanufactured is an important current problem. Under strong assumptions one can build Markov Decision Process (MDP) models for analyzing such systems. These models can be solved numerically at the expense of a significant computational effort if the state space is not too large. In order to develop fast and accurate methods that can approximately compute the optimal control policy and its parameters, and the corresponding cost performance, we employ a machine-learning based approach. To this end, we first build a labeled data set using numerical solutions of Markov Decision Process models of such systems for different combinations of input parameters and then test different learning algorithms that use the inputs as features, obtaining the hyper-parameters by cross-validation. The resulting approximations are fast enough to integrate into simulation-based on-line learning algorithms.

Key words: Manufacturing Flow Control; Remanufacturing; Markov Decision Processes

1. Introduction

Circular Economy encompasses supply chains that incorporate product returns, refurbishing and remanufacturing decisions as possible options or sometimes requirements (Dekker et al. (2013)). Making these decisions efficiently has significant economic and environmental consequences. A recent European research project AUTO-TWIN (https://www.auto-twin-project.eu/) proposes to investigate and aid such green gateway decisions by the aid of a digital twin of a manufacturing system.

Motivated by the potential of having a digital twin that can simulate an existing system, we explore methods for dynamic decision making for flows including returns and remanufacturing decisions. In particular, we investigate ideas for rapid and practical analysis for dynamic optimization that can be later integrated with simulation optimization.

A number of papers investigate basic models that include return flows and dynamic remanufacturing/coordination decisions. For instance, Vercraene and Gayon (2013) consider product returns and Vercraene, Gayon and Flapper (2014) investigate coordination of remanufacturing and returns acceptance.

The above papers and many others use Markov Decision Process (MDP) models of these systems. The MDP framework is formal and enables an understanding of the system but becomes impractical when the state space of the system grows or when Markovian assumptions may not hold. In this paper, we present some preliminary results that may eventually help obtain approximations for models with larger state spaces employing machine learning methods to enable learning of rules that estimate performance measures and policy parameters from inputs without the need for a numerical solution.

2. Models

2.1. Benchmark: A Capacitated Production/Inventory System without Returns

We consider a single-stage make-to-stock manufacturing system with a single processor (machine). We assume that demand arrives randomly according to a stationary Poisson process with rate λ, the processing times of the machine are exponentially distributed with rate μ. We assume that $\lambda < \mu$ for stability. When a product completes processing, it is placed in a finished goods inventory. When demand arrives, it is immediately satisfied from inventory whenever inventory is available. If no inventory is available, the arriving demand is backordered and waits in the backorder queue until a product becomes available. We assume that physical inventory incurs holding costs of h per item per time and backorders incur a cost of b per backorded item per unit time. This is a standard setup studied for instance by Buzacott and Shanthikumar (1993).

The typical dynamic production control problem is to decide when to continue production and when to stop depending on the inventory level. This well-established benchmark case has many advantages for testing purposes. The optimal policy is known to be a threshold type policy (a base stock policy). In addition, both the optimal threshold and the optimal cost have closed form expressions (Buzacott and Shanthikumar (1993)). In addition, the relative value function $w(x)$ can be numerically obtained by value iteration.

Machine Learning Approach for Quick Estimation

Since the important performance measures and policy parameters can be obtained expicitly, we can generate a labeled training data set where the input features are the parameters λ, μ, h and b and the targets are the corresponding optimal cost and the optimal threshold. One important remark is that both the optimal threshold and the optimal cost are highly non-linear functions of the inputs. We, therefore, test some non-linear estimation tools from machine learning to learn rules from the training data that estimate the optimal base stock level and the corresponding cost.

For the numerical setup, we generated the main dataset by systemically changing the parameter values (λ, μ, h, and b). The dataset was subsequently divided into training (80%) and testing (20%) segments. Utilizing 5-fold cross-validation, we tuned the optimal configuration for the Random Forest algorithm. The robustness of the model was tested across datasets with varying features and sizes, as summarized in the Table 1 below. In the table, we experiment with different training-test sizes and report the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE) for the cost estimation. We also report the threshold estimations that are within $\pm$ 1 unit of the true optimal threshold. Results indicate that, for this model the estimations perform well. More importantly, the model still produces satisfactory results even when only 50% of the data is used for training, and the rest for testing.

	(Train,Test) Size	(Train, Test) RMSE (g)	(Train,Test) MAPE (g)	$\lvert\hat{S} - S^*\rvert \leq 1$ (%)
Instance 1	(576,144)	(0.21,0.43)	(1.82,5.41)	(99.31,97.92)
Instance 2	(164,41)	(0.41,1.17)	(1.33,3.93)	(97.56,87.80)
Instance 3	(504,126)	(0.23,0.65)	(1.70,3.81)	(99.40,95.24)
Instance 4	(360,360)	(0.27,1.20)	(3.26,7.38)	(98.89,95.00)
Instance 5	(102,103)	(0.59,1,20)	(2.46,7.21)	(96.08,83.50)
Instance 6	(315,315)	(0.35,1.02)	(2.95,7.29)	(98,73,94.60)

Table 1. Performance of the Benchmark Model Across Diverse Datasets with Different Sizes.

2.2. A Capacitated Production/Inventory System with Returns

As the next test case, we consider a system with returns for which the performance measures cannot be computed analytically. Let us assume that the used items are returned at rate δ according to a Poisson process. These items can be accepted and placed in an input inventory for refurbishing or rejected at a cost. We assume that refurbishing requires the same processing as producing a new item and a refurbished item is as good as a new product.

Figure 1 presents the model without returns on the left and the one with the returns on the right.

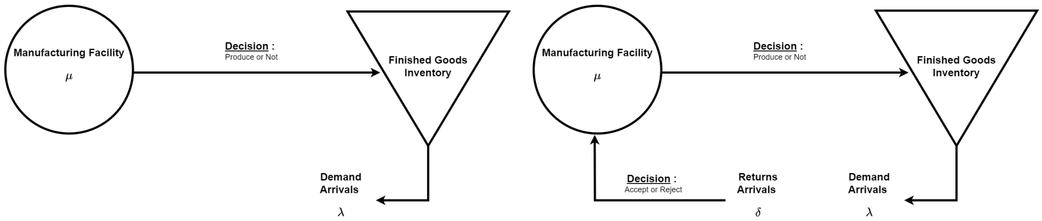

Figure 1. Models without (left) and with returns (right)

3. Conclusions

We propose and test a supervised learning approach to estimate performance measures of a production/inventory system. If such approximations can be developed robustly, they can be integrated within simulation optimization for dynamic decision making. The initial results look promising.

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