13th International Conference

on

Stochastic Models of Manufacturing and Service Operations

June 26 - July 1, 2022 Grenoble - France

SMMSO 2022

Program and abstract book

Welcome to the 13th Conference on Stochastic Models of Manufacturing and Service Operations SMMSO 2022 held at the conference center l'Escandille in Autrans, near Grenoble and located in the Vercors Massif of the French Alps.

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Program: SMMSO 2022, Grenoble – France - June 26 - July 1, 2022	
Sunday, June 26	
15:00 - 16:00	Welcome and Registration (Grenoble)
16:00 - 16:30	Opening Session
16:30 - 17:30	Keynote – *chair Maria DI MASCOLO* ***Alain PATCHONG*** *Founder & CEO of DILLYGENCE* Improving manufacturing systems engineering and operation in times of profound paradigm shifts in industrial value chains
18:00 – 20:00	Departure from Grenoble to Autrans
20:00 - 21:30	Dinner in Autrans (L'Escandille)
Monday, June 27	
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10:45 - 11:15	Coffee break
11:15 - 12:30	Session 2 - *Chair Siao Leu PHOURATSAMAY* • Solving Inventory Management Problems using Evolution Strategies ***Nima MANAFZADEH DIZBIN, Rob BASTEN, and Willem VAN JAARS*** • A novel analytical model for a single echelon inventory system under the (r, Q) policy ***Elisa GEBENNINI, Andrea GRASSI and Liberatina Carmela SANTILLO***
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10:45 - 11:15	Coffee break
11:15 - 12:30	Session 4 – *Chair Eric GASCARD* • *A Decomposition Approach for Stochastic Flow Lines with Provisioning of Auxiliary Material* ***Stefan HELBER, Carolin KELLENBRINK, and Insa SÜDBECK*** • *Hybrid modeling of manufacturing systems* ***Matteo MASTRANGELO, Maria Chiara MAGNANINI, and Tullio A. M. TOLIO***
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10:45 - 11:15	Coffee break
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12:30 - 14:00	Lunch
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Welcome message

Dear participants,

It is a great pleasure to welcome you to this Thirteenth International Conference on Stochastic Models of Manufacturing and Service Operations, SMMSO 2022, organized by G-SCOP Laboratory and Grenoble INP-UGA University.

This conference is the thirteenth in a row of successful conferences held every other year since 1997 in Europe. The conferences started in Greece (1997, 1999, 2001, 2003, and 2005) and moved to other countries (Netherlands, 2007, Italy, 2009, Turkey, 2011, and Germany, 2013) after returning to Greece in 2015, Italy in 2017 and in Germany in 2019.

Now, the conference has arrived in France, for the first time, and it is an honour and a great chance for us to gather you all in our mountains, after a so long period of online meetings.

We will have a rich program bridging research and practice in manufacturing and service operations, with a Keynote and 22 presentations, grouped into 9 sessions. This year, we are delighted to have Alain Patchong, Founder and CEO of Dillygence and Plateforme France Industrie 4.0 as our Keynote speaker. We thank him and all the authors, for their contribution to the success of the current conference.

We are grateful to the former organizers, and especially the initiator of these conferences, Christos Papadopoulos, who have managed to create this friendly atmosphere among the researchers of our network. We have also a thought for Yves Dallery, who was an active supporter of this conference since the beginning and passed away recently.

We would like to express our gratitude to our sponsors, CNRS (French National Center for Scientific Research), Grenoble INP-UGA University, and G-SCOP Laboratory.

Thank you also to the members of the scientific committee including J. Buzacott (York University, Canada), Y. Dallery (Ecole Centrale Paris, France), K. Furmans (KIT, Germany), S. Helber (Leibniz Universität Hannover, Germany), Y. Jang (KAIST, South Korea), F. Karaesmen (Koç University, Turkey), S. B. Gershwin (MIT, USA), G. Liberopoulos (University of Thessaly, Greece), A. Matta (Politecnico di Milano, Italy), S. Meerkov (University of Michigan, Ann Arbor, USA), C. Papadopoulos (Aristotle University of Thessaloniki, Greece), J. MacGregor Smith (University of Massachusetts, Amherst, USA), B. Tan (Koç University, Turkey), H. Tempelmeier (University of Cologne, Germany), T. Tolio (Politecnico di Milano, Italy) for their contributions in the preparation of the conference.

Finally, we would like to thank all contributors and their accompanying persons for participating in SMMSO 2022, and we hope you will enjoy your stay in our mountains and leave satisfied with your scientific and friendly discussions with other members of the SMMSO family.

The organising Committee of SMMSO 2022 :

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Keynote

Alain PATCHONG, Founder & CEO of DILLYGENCE and Plateforme France Industrie 4.0

Title: Improving manufacturing systems engineering and operation in times of profound paradigm shifts in industrial value chains

Abstract

Megatrends and global forces, like the pandemic and Russia's invasion of Ukraine, are causing profound changes in industrial value chains. This is leading to a sweeping redistribution of priorities, which is advancing manufacturing to the forefront of numerous governments' agendas. We are witnessing increased interest and investments in manufacturing as illustrated by the automotive and battery industries. Another important trend is the growing complexity of manufacturing epitomized by the emergence of gigafactories in these industries. Bigger investments means higher stakes. Therefore, it is now of paramount importance for industry decision-makers and professionals to possess practical tools that can help them design, support ramp-ups and operate factories optimally. These tools must help users navigate the complexity of the factory environment. Dillygence develops modern software for manufacturing systems design, improvement, and operation; and helps companies to use these tools. Much of the software is based on research that was presented at SMMSO meetings. Through presentation of use-cases, we will discuss how a mix of recent work from academia is being used to create abovementioned tools and help address industry needs effectively. Thereafter, we will share our perspective regarding future challenges, and the research areas that could be of interest for solving them.

Biography

Alain Patchong is the Founder & CEO of DILLYGENCE and Plateforme France Industrie 4.0, two companies at the heart of the transformation towards the industry of the future. Prior to starting Dillygence, he held several expert and executive positions at Faurecia, Goodyear, and Peugeot, including the role of Director of Assembly and Master Expert in manufacturing at Faurecia. He received the Edelman prize from the INFORMS in recognition of his work at Peugeot. Besides his industrial activities, Alain is very active in the academia as a senior lecturer at CentraleSupélec, where he established and managed a chair of manufacturing and logistics dually based at Technische Universität München (TUM). He currently teaches an Industry 4.0 course at CentraleSupélec and Paris Dauphine. He is also a former visiting Scholar at MIT. Alain is the author of several articles and books on industrial excellence and has been a member of several groups related to industry 4.0, including the France's Agence Nationale de la Recherche committee for the factory of the future.

Session 1

Chair: Horst TEMPELMEIER

Some-day instead of same-day deliveries: a stochastic-dynamic vehicle routing problem for alternatives in e-commerce delivery

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E-commerce retailers face the challenge of acting cost-efficient and becoming more sustainable at the same time, especially on the last mile, as the success of online retailers is strongly dependent on an efficient delivery to the customer. Retailers therefore offer a range of delivery options that differ in terms of speed. While the trend is moving in the direction of same-day and instant delivery, a new concept already adopted by Amazon is to offer a slow delivery option, too. Faster delivery modes increase total costs and emissions by leaving less time for efficient planning and limit consolidation possibilities on the last mile. Slowing down the delivery process offers the opportunity to increase shipment consolidation and thus save costs and take greater care of environmental demands simultaneously. The so-called "Some-Day-Delivery" option significantly increases flexibility in tour planning. We formulate the stochastic-dynamic Some-Day Delivery Problem (SDDP) that considers delivery deadlines as well as routing and capacity constraints in a multi-period planning environment. Our numerical study shows that forecasting future customer orders and their associated delivery options is critical to finding feasible routes, balancing capacity, and realizing consolidation opportunities.

Key words: last mile delivery; slow logistics; stochastic demand; stochastic optimization

1. Motivation and Problem Setting

Accelerated by recent trends like the Covid-19 pandemic, parcel deliveries are at an all-time high, mainly driven by the ever-increasing growth of e-commerce. Alongside the rising number of items ordered online, also the trend to even faster deliveries in the online business-to-customer (B2C) sector intensifies. A delivery time of one to three days from retailer to the customer's home remains the standard for the major part of deliveries, but same-day and instant delivery are currently the fastest growing segments. However, short delivery times put a tremendous pressure on traditional transportation networks and often result in less efficient distribution processes with poorly and unevenly utilized resources, greatly increasing the costs and emissions per parcel. In particular, this is caused by a lack of consolidation possibilities and little time for efficient planning. In this paper, we introduce a delivery concept for the B2C parcel delivery is discussed that aims simultaneously at decreasing delivery costs and increasing eco-efficiency. This can be achieved by intentionally slowing down the logistics processes in the course of parcel delivery and thereby allowing for more shipments being consolidated over a longer period of time. Amazon for instance already offers a slower delivery option in most regions of the US (Amazon 2021). In addition, recent studies show that route planning tailored according to customer availability avoids additional and thus unnecessary deliveries, thereby reducing delivery costs and CO_2 emissions (Voigt et al. 2021).

$$z_{ikt} = \sum_{j=0}^{N} x_{ijkt} \qquad \forall i \in N, k \in K, t \in T \tag{5}$$

$$\sum_{i,j \in S} x_{ijkt} \leq \sum_{i \in S} z_{ikt} - z_{jkt} \qquad S \subset C, \forall j \in S, k \in K, t \in T \tag{6}$$

$$\sum_{j=0}^{N} x_{1jkt} \leq 1 \qquad \forall k \in K, t \in T \tag{7}$$

$$\sum_{j=0}^{N} x_{j1kt} \leq 1 \qquad \forall k \in K, t \in T \tag{8}$$

$$x_{ijkt} \in \{0,1\} \qquad \forall i,j \in N, k \in K, t \in T \tag{9}$$

$$z_{ikt} \in \{0,1\} \qquad \forall i \in N, k \in K, t \in T \tag{10}$$

The objective function (1) minimizes transportation and inventory/waiting costs. Constraints (2) ensure that every customer is delivered within the requested delivery interval. Constraints (3) prohibit the vehicle capacities to be exceeded. Equations (4) conserve flow. Equations (5) link the assignment variables z_{ikt} with the flow variables x_{ijkt}. Constraints (6) are the subtour elimination constraints, formulated in terms of z_{ikt} variables. Equations (7) and (8) ensure that only one tour is performed per vehicle and day. Equations (9) and (10) define the variable domains.

We use the deterministic model formulated as the basis for our stochastic-dynamic modeling approach. In this context, we assume that only a subset of customer orders is known at planning instant. The additional customer demand within the planning horizon is predicted and therefore assumed to be uncertain and stochastic. New orders arrive at the end of each period, as customers place orders continuously over the planning horizon. A periodic re-planning is carried out each day to account for the newly arrived orders and the updated demand forecasts. The proposed solution approach is based on the established heuristics for similar settings used by Albareda-Sambola et al. (2014). We define customer types by geographical region and selected delivery option and estimate the expected necessary capacities on each day based on the set of known customers as well as the demand forecasts for future periods. We then determine a profit based on urgency, the probabilities of emerging customers in future periods and capacity utilization for each customer and solve a prize collecting VRP for the upcoming period.

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Two Dynamic Supplier Decision Problems when Buyer Visits Depend on Previous Service

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We study two dynamic supplier decision problems in which buyer visits depend on the previous service. In the first problem, we consider a supplier (he) serving several repeat buyers who generate different revenues and visit the firm with different average rates that depend on whether they are satisfied/dissatisfied with their last visit. Each period, the supplier must decide how many items to order before the demand is realized and which buyers to serve after the demand realization, if the demand exceeds the order quantity, to maximize his long-run average profit. In the second problem, we consider a repeat buyer (she) sharing her patronage among two heterogeneous suppliers. To enjoy the best service advantage, the buyer plays one supplier against the other by rewarding product availability with repurchase (loyalty) and punishing stockouts with switching (disloyalty) in the next period. Each period, each supplier (he) must decide how many items to order, knowing he has the supplier's loyalty. We consider two cases: one where the buyers compete, so each buyer aims to maximize his long-run average profit, and the second where the buyers cooperate, so their goal is to maximize the long-run average profit of the team. For both problems, we derive analytical and numerical results on the optimal policy of the supplier(s).

Key words: service-dependent demand; newsvendor; inventory policy; buyer selection; supplier selection; dynamic programming; game theory

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1. Problem 1: Dynamic Ordering and Buyer Selection Decisions

Make-to-stock suppliers with regular buyers must balance the cost of overstocking against the cost arising from the buyers' reactions when items are unavailable. In selecting which buyers to satisfy when shortages occur, they must weigh the current revenue from the satisfied buyers against the loss in future demand from the dissatisfied buyers. These reactions can vary significantly depending on the extent of the inconvenience that stockouts cause. In addition to diverse reactions to stockouts, buyers also have different margins due to customized pricing arising from differences in their market power, sales volume, etc. In the face of the buyers' heterogeneous demand dynamics and margins, firms must dynamically decide how many items to order in advance of demand, given that buyers may be at different satisfaction (goodwill) levels from previous encounters, and which buyers to select to satisfy if the order falls short of demand. These decisions require the careful balancing of the ordering cost, the current revenue from the satisfied buyers, and the loss in future demand from the dissatisfied buyers, raising several important questions for management: How many items should the firm order given the satisfaction levels of the buyers? When does future demand matter more than the current revenue in buyer selection? What is the interaction between ordering and buyer selection decisions? How sensitive is performance to each decision? How efficient is it to order a fixed quantity? How efficient is it to select buyers based o n a fixed prioritization?

To gain insight into these issues, we develop a newsvendor model of a firm that orders items for a group of repeat buyers. The buyers generate different revenues and have different average visit rates that depend on whether they are satisfied or dissatisfied with their last visit. If the demand exceeds the order quantity (current capacity), the firm must select which buyers to serve without violating capacity. We formulate the firm's problem as an average-profit Markov decision process (MDP) whose state is the vector of buyer satisfaction states and where the decisions are made in two stages: Before the demand is realized (ex-ante), the firm must decide its order quantity, and after the demand takes place (ex-post), it must select which buyers to serve. Using stochastic analysis, we characterize the myopic policy and the optimal policy for two buyers, and we provide some properties and conjectures on the optimal policy for multiple buyers. We also numerically compare three Lagrangian relaxation-based index policies for selecting buyers, where an index policy is defined as an ex-ante prioritization of buyers based on the value of some function (index).

The two papers that are most closely related to this work are Adelman and Mersereau (2013) and Klein and Kolb (2015). From a modeling point of view, the dynamic buyer selection problem that we consider can be viewed as a special case of a weakly-coupled dynamic program (Adelman and Mersereau 2008, Bertsimas and Mišić 2016) or a restless bandit problem (Whittle 1988). Such problems are known to be generally intractable, leaving heuristic policies such as Lagrangian relaxation-based approximations (Brown and Smith 2020) as the only practical alternative.

2. Problem 2: Dynamic Ordering Decisions under Competition/Cooperation

Many firms use dual or multiple sourcing strategies to hedge against operational and major disruption risks. Though having more than one supplier for the same items can add complexity and cost to a buyer, many of the risks of multiple sourcing can be mitigated by making sure that the buyer is working with high-quality suppliers. To this end, buyers develop procurement strategies based on which they select their supply partners. Once a supplier base has been created at the strategic level, the buyer must decide how to allocate the demand among the suppliers at the operational level. In many situations, the buyer can leverage the demand allocation decision to foster competition between the suppliers. One way to achieve this is to allocate the demand to the suppliers based on past performance. Most of the literature in this area is about firms that compete for market share on service, in a B2C environment. The share of each firm evolves smoothly as customers flow in and out of its customer pool depending on the service they receive from the firm and its competitors.

In this work, we focus on the abrupt switching behavior of a buyer from one supplier to another, following poor service, in a B2B setting, and its implication on the suppliers' competitive inventory policy. We develop a stylized model of a buyer doing business with two make-to-stock suppliers (we also discuss extensions to multiple suppliers) who provide a product to the buyer. There is little room for price differentiation, so the suppliers compete on the service they provide. One of the most important measures of service is product availability. To enjoy the best availability advantage, the buyer plays one supplier against the other by rewarding availability with loyalty and punishing stockouts with switching. The questions that we address are: What is the optimal inventory policy of each supplier in response to the other supplier's decisions? Do the suppliers' inventory policies reach equilibrium and if so, is it unique, and how is it related to their optimal inventory policy if they monopolized the buyer? Does the switching behavior of the buyer spark significant competition between the suppliers, and what is the optimal joint inventory policy of the suppliers if they decide to team up? Is it possible for one supplier to keep zero inventory and practically be driven out of the market? What do the suppliers gain in they cooperate and what does the buyer lose?

We find that the optimal ordering policy of each supplier is a basestock policy with a non-negative "active" basestock level when the supplier has the buyer's loyalty and a zero basestock level when he doesn't. Under competition, the optimal active basestock level of each supplier is greater than his myopic basestock level and is an increasing response function in the other supplier's active basestock level. Under a mild condition, the active basestock levels of both suppliers have at least one pure-strategy Nash equilibrium solution. If the suppliers cooperate, the optimal active basestock level of the supplier with the highest/lowest myopic profit is greater/smaller than his myopic basestock level. To get a more concrete apprehension of these results, we apply them to the case where the buyer's demand is exponentially distributed. This allows us to obtain exact expressions for the optimal active basestock levels and payoff functions, which we then use in a numerical sensitivity analysis. We conclude with a discussion of the extension of the results to more than two suppliers. This work draws mainly from two streams of research: newsvendor competition (Cachon and Netessine 2006, Silbermayr 2020) and inventory control under service-dependent demand (Hall and Porteus 2000, Olsen and Parker 2008, Liberopoulos and Deligiannis 2022).

Acknowledgments
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A two-stage stochastic programming approach for manufacturing systems configuration and reconfiguration

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Evolution of the industrial context leads to the need of manufacturing systems endowed with flexibility and reconfiguration capabilities, in order to be robust to changes in the production scenario. Therefore, manufacturing companies face a relevant risk when taking strategic decisions about which system resources should be acquired and how they should be operated, especially in presence of uncertain information about the future. This work integrates an approximate analytical model for performance evaluation into a two-stage stochastic programming approach for the optimization of configuration and reconfiguration decisions with alternative future demand scenarios, by means of linearized performance based on first-order hyperplanes.

Keywords: Manufacturing systems; Reconfiguration; Optimization; Stochastic programming

1 Problem statement and objective

This work presents a methodology for solving the configuration and reconfiguration problem for unreliable asynchronous serial lines. The methodology integrates an approximate analytical model for performance evaluation in a two-stage stochastic programming model, by means of a surrogate model for linearized performance expressed as a combination of hyperplanes.
The objective of the proposed methodology is to support the strategic decisions involving the design and operations of manufacturing systems in presence of uncertain information about the future. In particular, the problem of optimal configuration and reconfiguration under possible future demand scenarios is studied. First stage decisions define the acquisition of resources, i.e. machines and buffer capacities, as well as enablers for future decisions, whereas second stage decisions are related to additional buffer capacities and improvements in machine parameters which can be obtained.

2 Outline of the method

The proposed method is an iterative algorithm that integrates an approximate analytical model for performance evaluation of serial manufacturing lines into a two-stage stochastic programming problem by means of performance linearization.
The reference manufacturing serial line is composed of K machines and $K-1$ buffer and characterized by a unique production flow where no scrap and no rework is allowed. Each buffer has finite capacity equal to $N_k, k = 1, \dots, K-1$.
Each machine M_k is modeled as a continuous-time discrete-state Markov Chain (Magnanini and Tolio 2021). The properties of the throughput function are fundamental for the implementation of the majority of methods used to solve production line design problems. An extensive study on the throughput function has been proposed in (Gershwin & Schor, 2000). The main properties that shall be exploited are the following ones:

1. *Continuity*. The throughput function can be considered as a continuous differentiable function of buffer size $N_k, k = 1, \dots, K-1$, as stated in (Shi and Gershwin, 2009). Indeed, a small change in the buffer size causes a small change in the throughput.
2. *Monotonicity*. The throughput function of the system increases monotonically in each $N_k, k = 1, \dots, K - 1$. Hence, a small change in the buffer size causes a small *positive* change in the throughput, until the limit is reached.
3. *Concavity*. The throughput function is concave with respect to all buffer sizes $N_k, k = 1, \dots, K-1$.
4. *Limitation*. The throughput function is upper limited by the minimum production rate in isolation among the machines of the line.

The algorithm starts with the initialization (Step 0), i.e. setting of the target throughput in the first-stage period (th*) and in each future scenario s (th2$_s$*), the maximum capacity of each buffer ($maxcap_k$) according the physical constraints of the manufacturing line, and calculating the maximum possible throughput (thmax). If the problem is feasible, then the algorithm starts the iterative loop that consists of solving a the two-stage stochastic programming (2SSP) model in the Deterministic Equivalent Problem (DEP) formulation to obtain a candidate first-stage and second-stage decisions (Step 1) to minimize the total costs while guaranteeing the target throughput in all the possible scenarios. The 2SSP model includes an estimate of the throughput thanks to an approximation based on linear constraints. The candidate system configurations associated with the 2SSP solution of Step 1 (one configuration for the first stage and as many configurations as the number of scenarios for the second stage) are given as input to the performance evaluation model for an accurate estimation of the throughput (Step 2). The algorithm proceeds iteratively until convergence, i.e. when the throughput estimated by the performance evaluation for each candidate system configuration is greater or equal to the target throughput, while considering a tolerance (ε). If convergence is not reached, then first-order derivatives are extracted from the performance evaluation model and used to generate a constraint (throughput cut) linearizing the performance that is added to the 2SSP model (Step 3).
The method hence provides the optimal configuration decision for the first stage in terms of resources to be acquired and enablers, and for each second stage scenario the optimal reconfiguration decision in terms of additional resources or actions on the configuration parameters.

3 Conclusions and future developments

The proposed methodology integrates a performance evaluation methodology into a two-stage stochastic programming approach for the optimization of configuration and reconfiguration decisions in manufacturing systems design and operations. Linearized performance values are obtained grounding on an approximate analytical model where the first-order derivative of the throughput with respect to the buffer capacities and to the configuration parameters are used to define hyperplanes. These hyperplanes are then iteratively integrated as throughput cuts in the 2SSP model.

The structure of a two-stage stochastic programming model enables an additional level of problem decomposition that can improve the efficiency of the optimization. Indeed, Step 1 of the proposed algorithm can be revised by exploiting Bender's-type decomposition to separate the 2SSP model into a master program optimizing the first-stage decisions and several scenario sub-problems optimizing the second-stage decisions constrained by the first-stage decisions. Further cuts (i.e. optimization cuts) will be generated and added to the master program during the execution. The key advantage is that the all the throughput cuts generated in Step 3 will be added to the master program and each scenario sub-problem, thus speeding up convergence.

Further challenging research developments are represented by the application of the proposed hyperplane-based approach to more complex system topologies as split and merge, parallel machine configurations, closed-loop networks. In these topologies, the throughput function may have different properties with respect to monotonicity and convexity, hence the throughput cut based on the linearized performance should be adapted as a consequence. Moreover, the throughput function may be non-monotonic and non-convex also when complex control policies are applied within the system, with properties that may be not known a priori, thus increasing the complexity of applying the proposed hyperplane-based approach.

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Session 2

Chair: Siao Leu PHOURATSAMAY

Solving Inventory Management problems using Evolution Strategies

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Abstract

Reinforcement Learning (RL) agents have recently demonstrated their potential in solving sequential decision-making problems in inventory management. Recently, it has been shown that RL agents can learn to solve lost sales and dual sourcing problems with decent performance. However, the current applications of RL to inventory management problems require significant hyper-parameter optimization. We show that one can overcome this limitation using Evolution Strategies (ES). ES is shown to rival the performance of RL techniques on Atari and MuJoCo benchmarks. It is highly parallelizable, invariant to action frequency and delayed rewards, and has fewer hyper-parameters. In addition, the gradient-free nature of the ES makes optimization on non-differentiable objective functions and policy approximators possible. We show that one can use the objective function of the problem rather than defining policy, value, and entropy costs in finding the optimal control policy using a variant of ES called Covariance Matrix Adaptation Evolution Strategies (CMA-ES). CMA-ES can achieve near-optimal solutions with significantly smaller policy network architecture, in comparison to the neural network architectures reported in the literature, for controlling lost sales problem using the average reward per episode of these problems.

Keywords Inventory Management, Reinforcement Learning, Evolution Strategies, Optimal Control, Policy Optimization

1 Introduction

Reinforcement Learning (RL) agents have recently demonstrated their potential in solving sequential decision-making problems in various domains, such as playing Atari [1] and Alpha Go[2, 3] games. This suggests that RL agents could also be used to solve sequential decision-making problems in inventory management such as the lost sales problem. While exact algorithms solve small instances of these problems efficiently, they fail in solving larger instances in a reasonable amount of time due to the curse of dimensionality. Hence, researchers have usually designed heuristics for solving bigger-scale problems using the structural properties of the problem. Designing heuristics requires significant specialized knowledge about the problem. In addition, researchers usually make simplifying assumptions about the problem to come up with these heuristics, which limits their application areas. Therefore, using RL to find heuristics for solving sequential decision-making problems in inventory management seems promising.

RL methodologies are subclass policy and value function approximation methods for solving sequential decision-making problems modeled as a Markov Decision Process (MDP). Value function approximation methodologies estimate the value of being in a certain state, which then can be used in choosing the right action in that state. On the other hand, policy approximation aims at predicting the best action directly from the state. While the practice of using approximate policy or value functions in solving sequential inventory management problems has been around for a while, recently it has been shown to scale. Hence, RL methods are arising as a promising direction to learn heuristics for solving sequential decision-making problems. The main advantage of these algorithms is that they can solve different sequential decisions making problems without significant domain knowledge. However, this generality comes at the increased computational cost for learning the policy or value function approximators.

Recently, [4] show that it is possible to learn an RL agent to solve the lost sales problem with decent performance. However, the current applications of the RL to inventory management problems require significant hyper-parameter optimization. In this paper, we propose adopting alternative policy optimization methods with fewer hyper-parameters, namely Evolution Strategies (ES). Evolutionary methods have been shown to be a competitive alternative to RL methods for optimizing policy networks with several millions of parameters. [5] show that a simple variant of ES called the Natural Evolution Strategies (NES) can achieve similar performance to the RL methods on Atari and Mujoco environments. In this paper, we show that another variant of ES called Covariance Matrix Evolution Strategies (CMA-ES) can achieve near-optimal solutions on lost sales inventory management problem. CMA-ES performs a structured exploration on the parameter space of the problem by using the covariance matrix of the parameters of the policy function approximators. CMA-ES has shown descent performance on optimizing function with several hundred to several thousands of parameters. Such an scale of parameters maybe suitable for problems that arise in Operations Research and Operations Management.

In addition, ES has several advantages over RL methodologies. It is highly parallelizable, invariant to action frequency, and delayed rewards. In addition, the gradient-free nature of the ES makes optimization on non-differentiable objective functions and neural network outputs possible. We show that one can use the objective function of the problem rather than defining policy, value, and entropy costs. Our contributions can be summarized as follows:

- We show how to use gradient-free evolutionary methods to solve inventory management problems.
- We show CMA-ES can find policy function approximators that solve the lost sales problem with a descent performance using relatively low population size.
- We show CMA-ES can train significantly smaller neural networks that solve the lost sales problem in comparison to the neural networks presented in literature.

2 Solving lost sales inventory management problem using policy optimization

The Lost Sales problem is one of the fundamental problems in the inventory management literature [6, 7]. In this paper, we consider the standard lost sales inventory management problem with discrete time-steps and a single item. The demand and order quantities are assumed to be integer. The objective of the problem is to minimize the long-run average cost of the system, which consists of the lost-sales and inventory holding costs. The inventory manager has to decide on the number of products to be ordered (q_t) at the beginning of period $t \in \{1, 2, \ldots, T\}$ where T is the horizon of the problem. The ordered products will arrive in $L > 0$ periods from period t (in period $L + t$). Afterwards, the new set of products of size q_{t-L} ordered in period $t - L$ arrive. The arriving products are added to the current inventory increasing the inventory level to $I_t = I_{t-1} + q_{t-L+1}$ where I_{t-1} is the remaining inventory from period $t - 1$. The current inventory is used to satisfy the arriving demand of size d_t if there is enough inventory on hand, otherwise $d_t - I_t$ of the arriving demand is lost. Let h and p denote the inventory holding and lost-sales costs per unit per period. We assume the inventory procurement costs are zero without loss of generality. The objective of the problem is to minimize the long-run average cost of the system over the horizon of the problem which consists of T periods defined as:

$$\bar{C} = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} C_t, \tag{1}$$

where C_t is the inventory holding or lost-sales cost in period t defined as:

$$C_t = h[I_{t-1} + q_{t-L} - d_t]^+ + p[d_t - I_{t-1} - q_{t-L}]^+. \tag{2}$$

Our decision variable in this problem is q_t, the number of products to be ordered at the beginning of period t, for $t \in \{1, 2, \ldots, T\}$. In order to find the optimal values for q_t, we formulate the problem as an MDP. The state of the lost-sales problem in period t can be fully specified using the orders during the last L periods $(q_{t-L}, q_{t-L+1}, \ldots, q_{t-1})$ and inventory level of the problem at the end of period $t - 1$ as

$$S_t = (q_{t-L} + I_{t-1}, q_{t-l+1}, \ldots, q_{t-1}), \tag{3}$$

resulting in L dimensional state-space. We solve this MDP using policy optimization which aims to find a policy function approximator that decides on the number of products to be ordered. In this paper, we consider the linear combinations of the features and neural network policy approximators. The policy function approximators map the current state of the state into the probability of taking the actions in the action-space of the problem. The action-space of the lost sales problem consists of a set of discrete action in $\{0, 1, \ldots, \bar{q}\}$ representing the number of products to be ordered, where $\bar{q}$ is the maximum number of products that can be ordered.

Consider a policy function approximator π parametrized by θ demonstrated by π_θ from now on. θ consists of a vector of real numbers for the linear and neural network policy function approximators. A linear policy function approximator

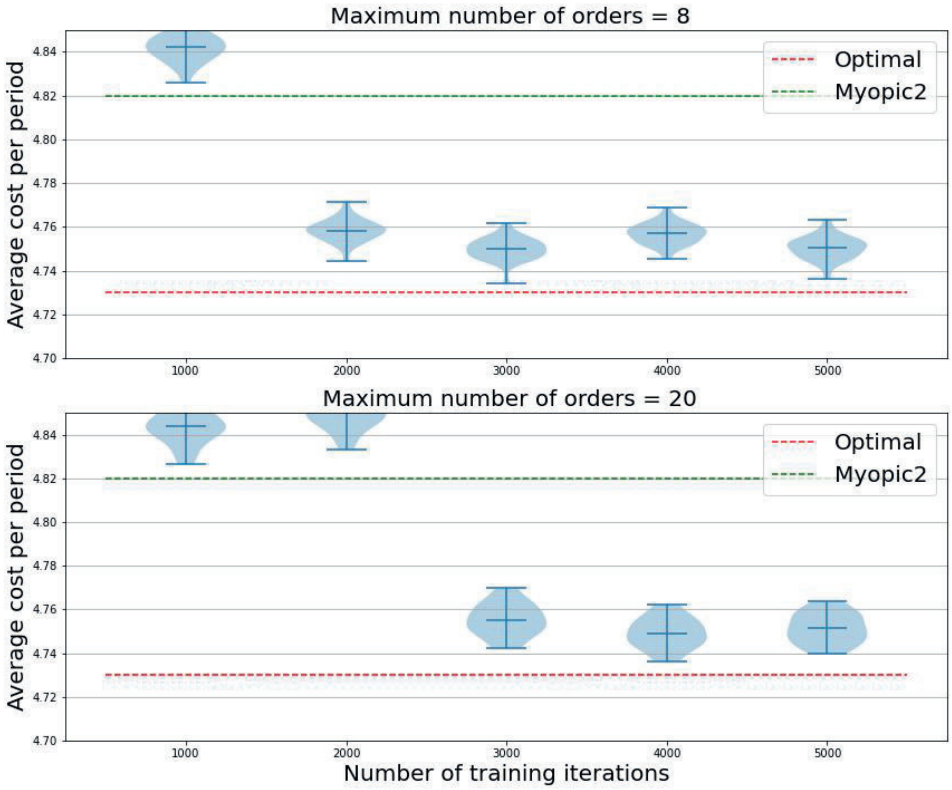

Figure 1: Performance of the linear policy function approximator in managing the inventory in a lost sales problem with lead time 4

determines the score of action q in the action-space by using a dot product of the current state of the system and set of weights $w_{1,q}, w_{2,q}, \ldots, w_{L,q}$. These scores are then used to calculate the probability of taking each action. It's parameters consists of a matrix of size $(\bar{q}+1) \times L$. Hence, θ can be represented as a $1 \times (\bar{q}+1 \times L)$ dimensional vector of real numbers.

Let S_1 demonstrate the initial state of the lost sales problem. We initialize S_1 by ordering a random number of products (less than maximum order size) for L periods. $\pi_\theta(S_t)$ determines the probability of ordering a given number of products when the system is in state S_t for $t \in \{1, 2, \ldots, T\}$. We choose the action with the highest probability as the number of products to be ordered. Our objective is:

$$\min_\theta \mathbb{E}\left[\sum_{t=1}^{T} C(S_t)|\pi_\theta)\right]. \tag{4}$$

In this paper, we use Covariance Matrix Adaptation Evolution Strategies (CMA-ES) [8] to optimize the parameters of the policy network. Figure 1 shows the performance of a linear policy function approximator in solving a lost sales problem with lead time of 4 and Poisson demand distribution presented in [6]. Myopic2 is one of the best performing heuristics for this problem [6]. Our results show that linear and neural network policy approximators can perform better than this heuristic in solving the lost sales problem.

3 Conclusions

In this paper, we show that one can use Covariance Matrix Adaptation Evolution Strategies (CMA-ES) as an alternative to Reinforcement Learning for solving sequential decision making problems in inventory management. We evaluate the performance of policy optimization using CMA-ES on lost sales problem. The linear and neural network policy function approximators found using CMA-ES results in a better average cost per period than the best performing heuristics for this problem.

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A novel analytical model for a single echelon inventory system under the (r, Q) policy

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This study presents an exact analytical modelling approach for the continuous-review (r, Q) inventory policy with lost sales. The aim is to obtain the closed-form expression for the state probabilities and the performance measures by applying recent advances in partition techniques for Markov chains.

Key words: Inventory model; stochastic model; reorder point; Markov chain

1. Introduction

Inventory models attracted the interest of both practitioners and scientists since a long a time. While early models were based on deterministic assumptions, more recent researches introduced the effect of variability on both the demand and the supply lead time (Zipkin 2000). Variability can generate stock-outs resulting in either lost-sales or back-orders, depending on the customer's willingness to wait for the order to be fulfilled. Safety stocks are then needed and correctly sized to reduce stock-out probability while keeping holding costs under control.

The most important approaches for inventory control are (i) the periodic-review policy, where the orders are placed at every occurrence of a fixed amount of time and (ii) the continuous-review policy, where a fixed-size order is released every time the inventory position reaches a pre-defined level called reorder point.

In general, as shown in the scientific literature (see, e.g. Bijvank and Vis 2011), the modeling of the lost-sales case is the most difficult to deal with because the lost demand per cycle produces a deviation in both the average inventory level and the inventory cycle time which is hard to estimate. Hence, the scientific community mainly concentrated on modeling the back-orders case (see, e.g. Kiesmüller et al. 2011), even though it is no longer fully representative of the the customer's behavior in modern industrial context. In addition, models addressing the lost-sales case (which are less common) often applies the periodic-review policy because it is simpler to be dealt with since the lost demand does not affect the inventory cycle time, which is fixed. Hence, a research gap persists with respect to studies on the exact modeling of the continuous-review inventory policy with lost sales.

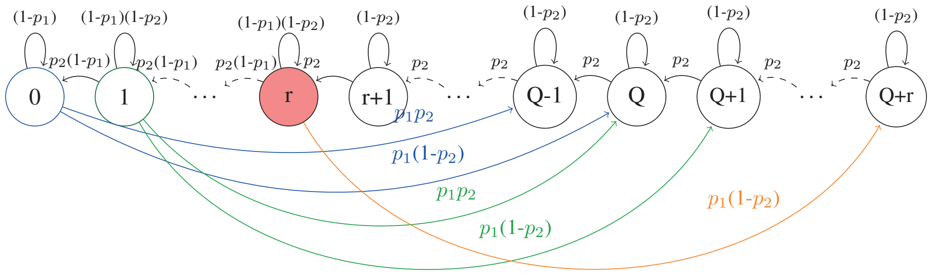

Figure 1. Transition graph for the single echelon system with (r, Q) inventory policy.

This study works towards addressing the aforementioned research gap by presenting an exact modelling approach for the continuous-review (r, Q) inventory policy with lost sales, which is the most adopted but also the most complex policy in several real-world applications. Specifically, a single echelon inventory system is modeled with the aim of determining the performance of the system as an analytical function of the order size Q and the reorder point r. Both the supply process on the upstream side and the consumption process on the downstream side are modeled by Bernoulli trials. The stochastic process is observed in discrete time intervals referred as ”time units” in the sequel. We assume that the occurrence of a consumption and/or a supply is evaluated at the beginning of any time unit; changes in the inventory level are evaluated at the end of the time unit. Specifically, in any time unit after an order has been placed (i.e., the inventory position at the beginning of the time unit is $n \leq r$), the supply process sends a lot of size Q with a constant supply probability and fails to do so with the complementary probability. We denote as p_1 the (constant) supply probability. The downstream consumption process can withdraw a single unit of material in any time unit. It is referred as ”item” in the sequel. Similarly as the supply process, also the consumption process is a Bernoulli process with a fixed consumption probability denoted as p_2. This means that in any time unit an item is withdrawn with probability p_2 if at least one item is available in stock or if a replenishment occurs at the beginning of the same time unit. When the consumption occurs, the inventory level at the end of the time unit decreases by one item. No consumption occurs with probability $(1 - p_2)$ in any time unit, or when the warehouse is out of stock and no replenishment occurs.

2. The model

The transition graph describing the discrete Markov process for a single echelon inventory system with (r, Q) inventory policy is depicted in Figure 1. The states of the system coincide with the inventory positions $n = 0, 1, \ldots, Q + r$. It can be noted that the maximum inventory capacity is $(Q + r)$ since the first inventory position at which a replenishment may occur corresponds to the reorder point $n = r$. As regards the transitions of Figure 1, it is possible to see that, e.g., state $(Q+r)$ can be reached in one time unit only from itself with probability $(1 - p_2)$ or from the reorder point $n = r$ if a replenishment occurs with no consumption (i.e., with probability $p_1(1 - p_2)$). Similar reasoning is applied to obtain the remaining transitions for state n, with $n = 0, \ldots, Q + r - 1$.

It is well-known that the discrete Markov chain corresponding to the transition graph of Figure 1 can be numerically solved by finding the state probabilities for given values of the parameters

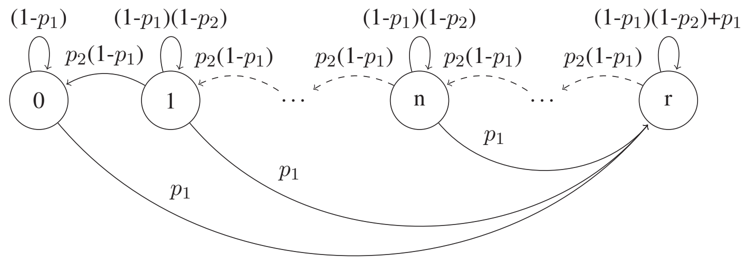

Figure 2. Partition-$[r]$ "in isolation".

p_1, p_2, Q, r. Nevertheless, the numerical approach becomes impractical when the state space is large. Moreover, only the derivation of a closed-form solution may allow efficient and rapid calculations which can be extremely useful for comparing different scenarios (e.g., with different values of the system parameters) and producing exact, compact and simple formulas for the most popular performance measures which are traditionally used for evaluating this kind of supply systems (such as the average inventory, the cycle time, the service level, etc.). Hence, the intent of this study is to describe the mathematical derivation of the closed-form expression for the state probabilities and the performance measures. The proposed approach is based on the *partition technique* firstly proposed by Gebennini et al. (2013, 2017). The basic idea is that, since the steady-state probability of entering a partition of states must equal the steady-state probability of leaving that partition and the partitions are mutually exclusive, it is possible to "isolate" each partition and solve the corresponding (simple) sub-chain as it were independent to the other partitions. Hence, the state probabilities "in isolation" can be computed and, then, combined in order to obtain the state probabilities of the original complex system.

Specifically, from the transition graph of Figure 1 it is possible to identify some homogeneous kinds of behavior, i.e. to identify some *state partitions* which correspond to smaller (and simpler) sub-chains. A first kind of behavior is expressed by states n with $n = 0, 1, \ldots, r$ which correspond to states at which a replenishment may take place. This sub-chain is called "Partition $[r]$" and can be represented by the transition graph of Figure 2 where the probability of leaving the partition (i.e., the probability of being in any state $n = 0, 1, \ldots, r$ and the replenishment occurs) equals the probability of entering the partition (that occurs at state r only). Other $r + 1$ state partitions (and the corresponding sub-chains) can be identified for inventory positions $n > r$. These partitions are called "Partitions $[i]$" where the index i, with $i = Q - 1, \ldots, Q + r$, identifies the inventory level reached after the replenishment. The reader may refer to the transition graph in Figure 3 which show the generic Partitions $[i]$ "in isolation", where the index i corresponds to the inventory level reached after the replenishment (i.e., the higher state in each partition).

Hence, a total of $r + 2$ partitions can be identified and the state probabilities "in isolation" can be computed. We denote as $\mathbf{P}(n)^{[r]}$ the probability "in isolation" of state (n) belonging to Partition $[r]$ "in isolation" and as $\mathbf{P}(n)^{[i]}$ the probability "in isolation" of state (n) belonging to the sub-chain related to Partitions $[i]$ "in isolation". It is also necessary to compute the probability for the system to be in each partition at any time unit, i.e. it is necessary to compute the so-called *partition probabilities*: $\Pi = \{\pi_r, \pi_{Q-1}, \pi_Q \ldots, \pi_{Q+r}\}$.

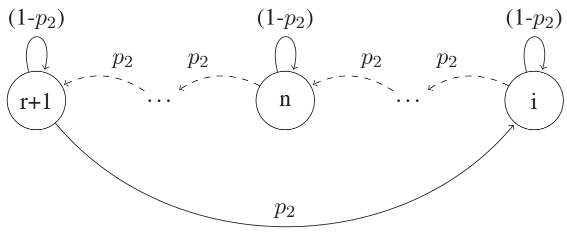

Figure 3. Partition-$[i]$ "in isolation", with $i = Q-1, \ldots, Q+r$.

Finally, the steady-state probability of any state n with $n = 0, \ldots, Q+r$ in the original system can be expressed as follows:

$$\mathbf{P}(n) = \begin{cases} \pi_{[r]}\mathbf{P}(n)^{[r]}, & n = 0, \ldots, r \\ \sum_{i=Q-1}^{Q+r} \pi_{[i]}\,\mathbf{P}\,(n)^{[i]}, & n = r+1, \ldots, Q-1 \\ \sum_{i=n}^{Q+r} \pi_{[i]}\,\mathbf{P}\,(n)^{[i]}, & n = Q, \ldots, Q+r \end{cases} \tag{1}$$

where

- states with $n = r+1, \ldots, Q-1$ belong to all the Partitions $[i]$ with $i = Q-1, \ldots, Q+r$;
- states with $n = Q, \ldots, Q+r$ do not belong to all Partitions $[i]$, but only to a subset of them, i.e. only to Partitions $[i]$ with $i = n, \ldots, Q+r$. For example, state $n = Q$ does not belong to the partitions whose maximum inventory level is lower than Q.

3. Conclusions

This paper proposes a novel analytical model for the single echelon inventory system with (r, Q) inventory policy. The main objective is to provide the reader with simple closed-form expressions of the state probabilities by applying recent advances in *partition techniques* for Markov chains. Hence, the state probabilities and the most popular performance measures can be simply expressed as a function of the system parameters $p1, p2, r, Q$ without the need of explicit state-space and action-space enumeration.

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Session 3

Chair: Cathal HEAVEY

Neural network based approaches for stochastic production line performance control

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To stay competitive, modern market scenarios are forcing a radical shift in the manufacturing concept, focusing companies' attention on customer satisfaction through increased product customization and quick response strategies. Taking advantage in recent innovations in the use of neural networks, this paper proposes two different training approaches for implementing WIP based throughput control of a stochastic production line. Simulation based scenarios show the effectiveness of the implemented methods.

Key words: production line; deep neural network; stochastic modeling; performance control

1. Introduction

The ability to meet increasingly personalized market demand in a short period of time and at a low cost can be viewed as a fundamental principle for the competitive revival of industrialized countries against emerging countries with lower technological development but lower social and labor costs. In this context, it is critical to develop the ability to efficiently use available resources, as well as the ability to rethink and revolutionize production process methods and control approaches in order to respond appropriately to new market challenges (Fogliatto et al. 2012).

Several control strategies based on autonomous and independent control principles have been proposed in the scientific literature (Dolgui et al. 2019). However, these control strategies need significant changes to the production system, whereas manufacturing firms are still looking for a more simple solution capable of controlling the Work-In-Progress (WIP) level while monitoring the system's throughput. One of these solutions could come from the CONtrolled Work-In-Progress (CONWIP), proposed by Spearman et al. (1990).

The correct tuning of WIP is critical for the manufacturing system performance. When variability is present, a high level of WIP ensures a higher value of throughput at the expense of a longer time required for a job to traverse the production system. On the other hand, low levels of WIP ensure that production jobs cross more quickly, at the expense of the throughput. As a matter of fact, it is convenient to have a production system able to dynamically change the amount of WIP, depending on the level of variability in the system.

In this regard, the purpose of this work is to develop joint stochastic and neural network approaches for production line performance optimisation capable of accounting for the variability of processing time entering the production system, once a given throughput to achieve is known. Hence, the output of the proposed approaches is the estimation of the minimum amount of WIP to be set in the production system for achieving the requested throughput while safeguarding the delivery time.

2. Problem Statement and Proposed Approaches

Without sacrificing generality, consider a flow-shop production line that is controlled by a CONWIP mechanism and formed by single-machine production stations. Components (i.e. jobs or work-in-progress) can be considered units representative of reasonably quantifiable processing batches (i.e. number of jobs or parts being processed in the line). As a result, we will focus on a single-product, single-routing production line in which the only source of variability is job processing times. We chose to generate job processing times for the training scenarios using a gamma distribution with shape parameter alpha (α) and scale parameter beta (β). The variability introduced in the system can then be varied acting on the α parameter, so as to model both high variability scenarios (i.e. those involving customized production) and low variability scenarios (i.e. those involving standardized production) can be easily identified (Grassi et al. 2021).

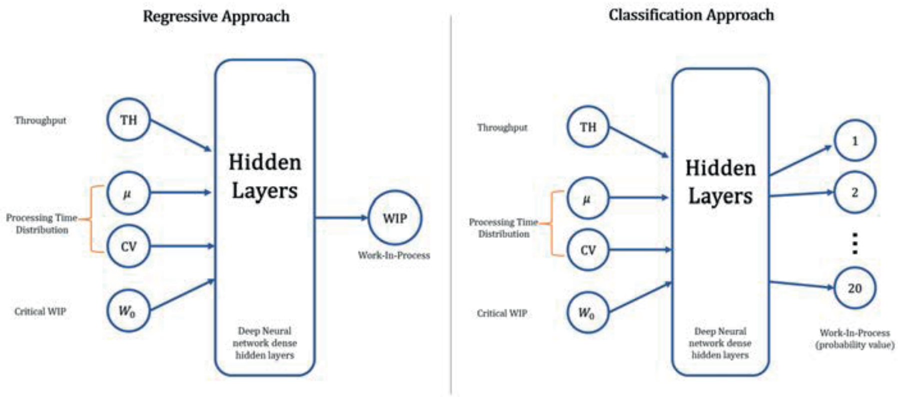

Figure 1. The proposed neural network approaches

Nonetheless, for the performances optimisation approach to be found, mathematical models relating WIP to the given throughput are required. There are some attempts in the literature to identify these models, but these approaches are valid only in the most restricted case of exponential processing time variability (Grassi et al. 2021, Spearman et al. 1990). A recent work by Vespoli et al. (2021) proposed a control strategy incorporating stochastic knowledge and a PID-type control approach. While the obtained results are quite interesting and broadly applicable, the resulting control action response is quite slow to changes due error feedback based behavior of the PID control strategy. To address this limitation, we propose the use of neural network-based approaches for estimating the level of WIP to be set within the production system, once the characteristics of the variability of input processing times and the configuration of the production line under consideration are known.

In this regard, we propose two distinct approaches, as depicted in Figure 1: a first approach (on the left) in which the neural network operates in a regressive mode, identifying in closed form the value of WIP required to obtain the input value of throughput; and a second approach (on the right) in which the neural network operates as a classifier, providing as output the probability that a particular situation should be controlled with a defined value of WIP. Both networks accept as input the desired throughput value, two information about the sample distribution for waiting and processing jobs (e.g. the average processing time and the coefficient of variation, calculated as the standard deviation divided by the mean) and the number of production stations of the considered production line. The first configuration returns the level of WIP (which can also be decimal and will thus be approximated to the nearest whole number), while the second configuration returns a probability value (here, limited to 20) where the position of the node is directly related to the amount of WIP to be set on the production system.

To begin training this type of models, however, a large amount of data must be collected. To this extent, a simulation model was created using the Discrete-Event and Agent-Based techniques in conjunction with the Anylogic simulation software. To gather all of the required data, the model was run for various values of variability (i.e., varying the $alpha$ value of the processing time distribution at a step of 0.1 for values between 0.5 and 3) and WIP (i.e., varying it between 1 and 20), for a simulation time of 4 years (to ensure that the steady state is reached), and replicated 40 times for each parameter combination.

After setting the network input and output architecture and the network hyper-parameters, such as the number of neurons inside the hidden layer, their activation functions and loss function were determined. Regrettably, no objective method exists for selecting these parameters (Patterson and Gibson 2017). As a result, the network has been scaled using a “trial and error” methodology. The neural network model was developed using the Tensor Flow Keras library on Google Colaboratory. The training dataset consisted of 20800 data points extracted from the simulator and was divided into three sections: training (75%), validation (20%), and test (5%).

3. Discussion and Conclusions

Following the training phase, experiments to validate the outputs of both approaches has been conducted. This was accomplished by setting up the same simulator previously used for data collection in execution mode. Once the values of variability for the processing times and the desired throughput have been defined, they have been used for estimating the WIP value to be imposed on the productive system. Both models showed superior forecasting capabilities, enabling much more precise sizing of WIP than was previously possible, even in scenarios when the memoryless assumption is relaxed.

The promising results obtained with the presented approaches suggest to continue the research in the integration between stochastic models and artificial intelligence techniques.

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A Machine Learning Approach to the Performance Evaluation of Time-dependent Queues

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Many of the systems traditionally modeled using queueing theory operate in time-dependent environments. For this reason, the fast and accurate estimation of the performance of time-dependent queues is of great interest. With the recent advances in the field of machine learning, its highly accurate modeling tools can be utilized for the analysis of time-dependent queues. In this work, we propose an algorithm that imploys pre-trained models of the transient behavior of queues iteratively to estimate time-dependent behavior. In addition, by using conditional expectation, our algorithm estimates the coefficient of variation (CV) of the queue length. With both the mean and the coefficient of variation of the queue length available, the algorithm is able to estimate the distribution of the queue length which in turn can be used for calculating waiting times. Furthermore, given that the output functions of machine learning models might not have the properties desirable in the performance of a time-dependent queue, we propose an explainable modeling approach. This modeling approach uses the highly accurate machine learning predictions as a starting point and builds a model with desirable characteristics based on them. Using extensive numerical experiments, we show the accuracy and efficiency of the method proposed here.

Keywords: Time-dependency; Machine learning; Queuing

Performance Evaluation of Manufacturing Systems by Joint Use of Analytical Models, Simulation, and Supervised Learning

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Designing and controlling complex production systems effectively requires fast and accurate performance evaluation tools. We present an approximation approach that uses analytical models, simulation and supervised learning jointly. The proposed method decomposes a given manufacturing system into a number of inter-connected building blocks similar to the other approximation methods. Each block is evaluated with its own parameters that describe the service characteristics together with the parameters that describe the part arrivals and the possible interruptions due to starvation and blocking. The output of each block gives the characteristics of the arrival and flow interruption processes. These output characteristics are then passed to the connected blocks and the process is continued until a convergence criterion is met. As opposed to the literature where an analytical method is used to determine the output parameters of a building block, our proposed approach uses analytical models, simulation, and supervised learning that yield the desired output parameters when the input parameters are provided. Our results show that this approach gives fast and accurate predictions for manufacturing systems that cannot be analyzed by using the existing analytical approximation methods.

Keywords: performance evaluation; simulation; supervised learning

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1 Introduction

Production systems and supply chains that can meet orders in a short time with a shorter cycle time, a higher throughput, lower inventory levels and utilize material and energy resources efficiently improve competitiveness. In order to design such production systems and supply chains and control them in an effective way, there is a need to develop a fast and accurate method for evaluating the performance of the system operating with a given design and a control policy. These methods that are used in the Digital Twins of production systems and supply chains, use analytical approaches or simulation. While the performance evaluation methods that are based on the analytical models are very fast, their accuracy depends on the fit between the underlying assumptions and the system being analyzed. Similarly, while the simulation models can be used to analyze any given system, developing the models and running the simulations to obtain statistically significant results can take a long time and may require significant computing resources.

We present a methodology to develop algorithms that yield *fast* and *accurate* performance evaluation of material flows in production systems and supply chains in a data-driven way under more general assumptions. The novelty in this approach is proposing *a new methodology* for solving *new problems* to the literature on design and performance evaluation of production systems. The *new method* proposed by this approachs is analyzing a given system by using an analytical decomposition algorithm together with the trained models obtained with machine learning in advance and using these models in design algorithms. The models are trained with an approach that combines analytical modeling, optimization, simulation and supervised learning methodologies that are implemented with high performance computing. This approach contributes to the literature by being more *accurate* compared to the analytical methods, *faster* compared to simulation, and its ability to use previously trained models without requiring the creation of new training data for new systems compared to the machine learning methods.

2 Supervised Learning Based Queueing Network Analysis

The method we propose, referred as the Supervised-Learning based Queueing Network Analysis (SLQNA) follows the analytical approximation methods that have been developed in the literature (Dallery and Gershwin, 1992). That is, the method decomposes a given manufacturing system into a number of inter-connected building blocks similar to the other approximation methods. Each block is evaluated with its own parameters that describe the service characteristics together with the parameters that describe the part arrivals and the possible interruptions due to starvation and blocking. The output of each block gives the characteristics of the arrival and flow interruption processes. These output characteristics are then passed to the connected blocks and the process is continued until a convergence criterion is met.

Figure 1 shows the general delay block that is used to construct a given manufacturing system together with other blocks including split, merge, and batching. In this block, the parts arrive with an interarrival time process summarized with the first two moments of the interarrival time distribution and an exponentially decaying autocorrelation function with a given first-lag autocorrelation. There are N parallel servers. The service time process for each station is also determined similarly with the mean and the coefficient of variation of the service time distribution and the first-lag autocorrelation. The parts are processed according to the sequencing rule S that can be first come first served, last come first served, shortest processing time, longest processing time or service in random order. The input buffer can be infinite or finite with a given capacity. The output of the block can be subject to blocking due to an inter-connected finite buffer. If the output can be blocked. The blocking process can be modelled in different ways. In its simplest form, a blocking probability and the mean and the coefficient of variation of the blocking removal time approximate the blocking process. In this building block, there are 11 inputs (μ_a, cv_a, ρ_a, μ_s, cv_s, ρ_s, S, N, b, cv_b, ρ_b) and 9 outputs. The outputs are the characteristics of the departure process (μ_d, cv_d, ρ_d), the mean, coefficient of variation and the quartiles of the cycle time (CT, cv_{ct}, q_{ct}) and the blocking probability and the meand and the coefficient of variation of the blocking removal time for its upstream (b^u, μ^u_b, cv^u_b).

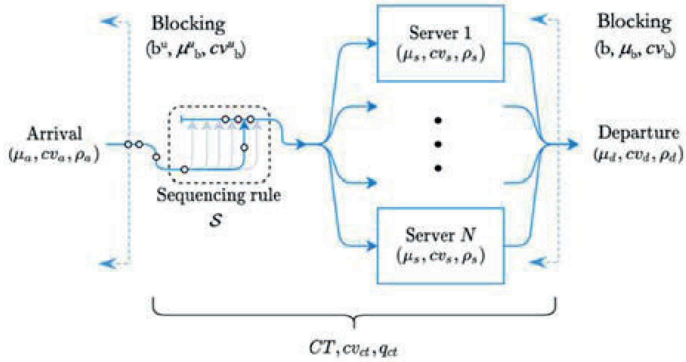

Figure 1. The General Delay Building Block

As opposed to the literature where an analytical method is used to determine the output parameters of a building block, we propose using different methods that yield the desired output parameters when the input parameters are provided.

In the Supervised Learning Based Queing Network Analysis (SLQNA) approach we developed recently, first the training data for a supervised learning algorithm is generated by simulating the dynamics for different blocks for a wide range of system parameters (Khayyati and Tan 2021a, 2021b). We use parallel computing to obtain the training set in a high performance computer cluster. Then, a supervised learning algorithm is used to predict the output characteristics of the blocks by training the algorithm with the training data. In SLQNA, Gaussian Process Regression is used as the supervised learning algorithm due to its superior performance with noisy data obtained by simulation (Rasmussen and Williams, 2006). Finally, the output characteristics are fed into the following block to analyze a queueing network.

In this approach, the training for a given block is done only once. Once the training data is obtained by using simulation and a prediction model is trained, the trained model is added into a library and used whenever it is necessary to decompose a given manufacturing system. With this approach, the trained model replaces an analytical model to analyze a given building block and the output parameters can also be obtained in a short period of time. Figure 1 shows the distribution of the computational effort in SLQNA.

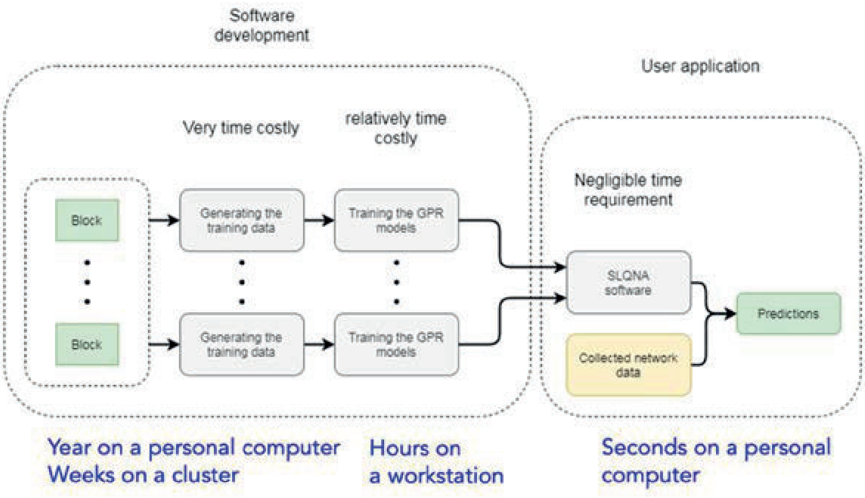

Figure 1. The distribution of the computational effort in SLQNA

In our earlier work, we developed the building blocks for a multistation work cell operating under different service disciplines with infinite input buffers, batching, split and merge with correlated interarrival and service times with Weibull distributions. The building blocks for a multistation work cell operating under different service disciplines with finite input buffers and the approximation algorithms for systems subject to blocking with loops are being developed. Our preliminary numerical results show that the proposed method works successfully and yields accurate predictions in a short time.

3 Conclusions

We present a method that extends the analytical approximation methods that are based on decomposition to using general building blocks that are analyzed by using supervised learning models trained with simulation. This approach yields fast and accurate predictions about the performance of a manufacturing system that cannot be analyzed by using the existing analytical approximations.

Our results for manufacturing systems that can be modelled as open queueing networks without blocking show that the proposed approach predicts the performance measures twice as accurately, and 150-times faster compared to the most accurate approximation methods available in the literature. Our preliminary results for manufacturing systems that can be modelled as queueing networks subject to blocking show that this is a promising approach that combines accuracy of simulation with the computational efficiency of analytical approximations.

This approach can be extended where different approaches are used to evaluate the performance of various blocks that are used to decompose a manufacturing system. For example, a building block can be analyzed analytically, another one can be analyzed by using the supervised learning or by using simulation.

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Session 4

Chair: Eric GASCARD

A Decomposition Approach for Stochastic Flow Lines with Provisioning of Auxiliary Material

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1 Problem Description

In this paper, we consider a model of a stochastic flow line with buffers of limited size between adjacent machines at the respective production stages. As in previously published papers, we assume random processing times, random times to failure and random repair times, see Papadopoulos, Li, and O'Kelly 2019 for a recent overview. The additional feature characterizing this paper is a further random process directed at the provisioning of auxiliary material at the production stages. An example of this auxiliary material could be components that are mounted on the work pieces as part of the assembly operation performed at the respective production stage. In practice one can find storage facilities such as racks or shelves next to the machines in which the auxiliary material is temporarily stored. As the auxiliary material is being depleted during the assembly operation, new material has to be provisioned in a regular manner, often using specialized transportation systems such as automatic guide vehicles (AGVs). Upon arrival of such a vehicle, the local storage of the auxiliary material gets re-filled to a predetermined order-up-to level. This leads to important design questions. On the one hand, it is not attractive to have over-sized local storage systems, in particular as they require valuable floor space. On the other hand, overly frequent replenishment operations place a heavy burden on the transportation system used to bring the auxiliary material to the flow line, which can also be costly in terms of required vehicles and furthermore lead to congestion in the internal transportation system.

Figure 1 depicts an schematic representation of the flow line model considered in this paper. Squares indicate machines and circles represent buffers. The model is based on the following assumptions: The work pieces travel through the system from the left to the right and leave the

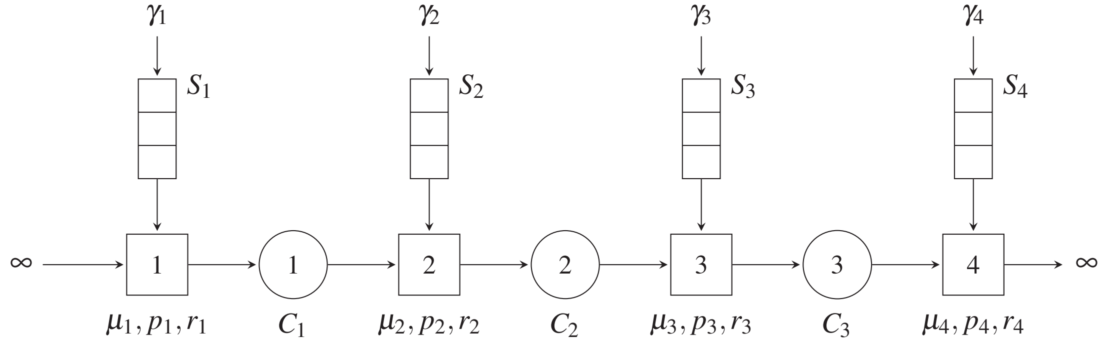

Figure 1: Example of a four-machine flow line

system again when the process on the last machine has been completed. Upstream of the first machine, there is an infinite supply of work pieces to be processed. Likewise, there is an infinite space downstream of the last machine. An upstream machine can hence never be starved and a downstream machine can never be blocked. The system can therefore be analyzed in isolation from its surroundings.

Processing times at machine i are exponentially distributed with rate μ_i, as are times to failure with rate p_i and repair times with rate r_i. The buffers i between adjacent machines i and M_{i+1} can hold up to C_i work pieces. We assume *blocking after service* (BAS), i.e., if upon process completion at machine i the buffer downstream of machine i is full, the processed work piece remains on machine i which is then blocked.

While a machine operates, it can fail with rate p_i, i.e., we assume operation-dependent failures (ODF). In other words, a machine that is blocked or starved cannot fail. For each operation on a work piece, the machine requires one unit of the auxiliary material, e.g., a component to be mounted to the work piece. The auxiliary material is brought to machine i with exponentially distributed inter-arrival times with rate γ_i. Upon arrival of the transport of the auxiliary material for machine i, the local level is raised up to the order-up-to level S_i. (In a practical setting, we typically find $S_i \gg 1$ and hence $\gamma_i \ll \mu_i$).)

Analyzing such a system is a non-trivial task, in particular if the randomness stemming from processing, failures, repair, and material provisioning together drives the performance of the flow line. For this reason, we propose a Markovian model of such a flow line by assuming the that all the times follow individual exponential distributions. In this attempt, we encounter the typical problem of the explosion of the state space. For this reason, we use a decomposition method as proposed by Choong and Gershwin 1987 to numerically analyze the system. The building block of the decomposition is a two-machine model. In previously proposed decomposition methods for stochastic flow lines, it typically turned out to be unproblematic to solve the two-machine model, i.e., to quickly and exactly determine the steady-state probabilities and, subsequently, performance measures such as long-term throughput, blocking and starving probabilities, since the state space of the two-machine models was typically rather small.

In our case, however, this is no longer true. The size of the state space of the two-machine model can become so large that analyzing the two-machine system becomes a problem which requires special attention. This is an important problem since, for the analysis of longer lines via an iterative decomposition approach, we need to solve two-machine models frequently, quickly, and accurately. We use a Gauss-Seidel (GS) approach to determine the steady-state probabilities of the two-machine lines numerically. As a methodological alternative, we also trained a neural network based on performance data for two-machine lines and then used this neural network to predict the relevant performance measures and state probabilities inside of the decomposition approach for the longer flow lines with more than two machines.

Our paper contributes to the research on manufacturing system in multiple ways. First, we add the modeling component of exponentially distributed inter-replenishment times of the auxiliary material to the Markovian model of unreliable flow lines with random processing times, times to failure, and repair times. For the case of the two-machine model, we give a detailed description of the resulting continuous time Markov chain (CTMC) model and show how to determine steady-state probabilities and performance measures numerically, in spite of the relatively large state space of the two-machine model. We furthermore show to which extent those values can be predicted by a neural network. Second, we show how the decomposition for longer lines proposed in Choong and Gershwin 1987 can be adapted to deal with the new flow line feature. Third, we use the models to study the delicate interactions of the different sources on randomness on the one hand and design parameters such as buffer sizes, order-up-to levels, and delivery frequencies on the performance on the flow line. This helps to develop intuition as to the conditions under which the provisioning process for the secondary material has a major impact on the line.

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Hybrid modeling of manufacturing systems

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Rapidly changing market conditions and frequent disruptions force manufacturing companies to perform frequent reconfiguration of their systems, usually made of different production areas that are strongly integrated among each other. In this context, the ability to rapidly modify not only the configuration of the physical part but also the configuration of the cyber counterpart is crucial to ensure proper decision making and short reaction times. This work proposes a hybrid method for steady-state performance evaluation of large complex systems, integrating sub-system models that are independently developed according to the modelling approach that is bet suited to representing the characteristics of the sub-system. Alternative configurations can be evaluated by modifying, or replacing, portions of the system model, without the need of acting on complex monolithic models, therefore increasing model maintainability and re-use. Integration of sub-models is obtained through Remote Models, that are a synthetic state-based representation of the blocking and starvation dynamics at the boundaries of each sub-model. State transitions in the remote models capture the distribution of transition times, that may consist of both deterministic and stochastic components. Final performance evaluation of the complete system is obtained through a generalized decomposition algorithm able to integrate both analytical Markovian models and discrete event simulation models.

Keywords: Manufacturing systems; Performance evaluation; Hybrid modelling

1 Problem statement and objective

This work presents a method for steady-state performance evaluation of manufacturing systems through a hybrid approach that combines analytical Markovian models and discrete event simulation models. The proposed hybrid method is devoted to the evaluation of strategic configuration and reconfiguration decisions. The frequency with which companies are forced to reconfigure their systems is constantly increasing, due to rapidly changing market conditions and frequent occurrence of disruptions. Therefore, system models need to be easily maintainable and reconfigurable and must allow re-use of existing models.

The reference system for the proposed modeling approach is a large production system composed of different areas dedicated to different operations. For instance, a production system may have a machining area, an assembly area, a testing area and a packaging area connected by material handling and transport equipment. In this type of integrated production system every area may have its own model, which may be developed independently from the others with the approach that is best suited to represent its characteristics. For example, analytical performance evaluation models available in literature can be adopted to model production areas that are structured as flow lines, while AGV fleets and transport systems may be modeled with discrete event simulation models, either developed on purpose or available from past simulation studies.

The integration of multi-paradigm models has been used by researchers to exploit modeling functionalities that cannot be captured with a unique approach, as in the integration of Discrete Event Simulation (DES), System Dynamics (SD) and Agent Based Simulation (ABS) (Brailsford (2019)). Examples of application of distributed simulation based on known standards as the High Level Architecture (HLA) can be found in Pedrielli et al. (2012) for the analysis of production systems, in Anagnostou et al. (2013) for the analysis of medical emergency services, or in Medina et al. (2013) for the analysis of maritime logistics. These approaches focus at single entity level and aim at runtime synchronization among models, which makes them suitable for short-term analysis. In medium-term analysis instead, the steady-state performance of the system is of interest. Therefore, there is no need for runtime synchronization among models and integration of analytical and simulation models becomes possible. A first classification of hybrid analytical/simulation models was provided in Shanthikumar and Sargent (1983). Examples of application of hybrid models can be found for performance evaluation, using simulation either to overcome approximations present in analytical models or to model features that cannot be analytically modeled, or for system control, combining simulated performance evaluation and analytical control models. Other areas of application of hybrid modeling include the integration of simulation models and mathematical programming for optimization, as in Frazzon et al. (2018), multi-scale modelling with vertically integrated models of the same system focused at different levels of detail, as in Terkaj et al. (2021), or performance evaluation based on multi-fidelity meta-models, as in Lin et al. (2019). The proposed approach aims at the the horizontal integration of models according to material flow paths for performance evaluation of manufacturing systems.

2 Outline of the method

The proposed hybrid method is based on the decomposition of a given large manufacturing system in a set of sub-systems that can be identified according to the different types of operations performed on the workpiece. Once sub-systems are identified, independent analytical or simulation models are developed for each of them. Every sub-system model is a different System View, i.e. represents the behavior of the whole system cenetered on a specific sub-system. Therefore, each System View must include both the detailed analytical or simulation model of the sub-system of interest and Remote Models that mimic the dynamics of other sub-systems, accounting for reciprocal limitations that sub-systems exert on each other. The number of Remote Models present in each System View depends on the physical connections with neighboring sub-systems through material flow paths.

The Remote Model is a state-based model that synthetizes the dynamics of a given sub-system at its borders. It captures starvation limitations propagating towards downstream sub-systems and blocking limitations propagating towards upstream sub-sytsems. Observing the behavior of a specific machine it is possible to notice that blocking and starvation limitations can be both deterministic and stochastic. Deterministic (or quasi-determistic) limitations can be observed in asynchronous automated systems, where processing times can be considered deterministic. The difference in speed among neighboring automated machines causes deterministic cycles in machine states, where faster machines get cyclically blocked or starved after process completion of every part, waiting for the slowest machine to complete processing. Combination of different deterministic processing times yields deterministic residence time in operational and blocking/starvation states. Stochastic limitations are caused by occurrence of random events, such as failures, interrupting material flow, and by stochastic processing times, in case of manual operations.

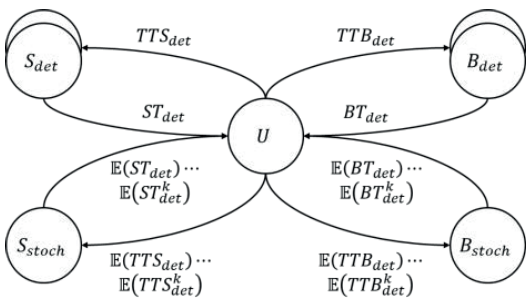

Figure 1. Representation of the state-based remote model

Figure 1 provides a representation of the state-based Remote Model, where:

- State U represents the operational (up) state, where the sub-system is operating with no limitations.
- States B_{det} and S_{det} represent the deterministic blocking and starvation limitations and are characterized by the deterministic time to blocking/starvation, TTB_{det} and TTS_{det}, and the deterministic blocking/starvation time, BT_{det} and ST_{det}.
- States B_{stoch} and S_{stoch} represent the stochastic blocking and starvation limitations and are characterized by the distributions of the time to blocking/starvation and of the blocking/starvation time. Distributions are synthetized through the first k moments, $\mathbb{E}(TTB_{stoch}) \dots \mathbb{E}(TTB_{stoch}^k)$, $\mathbb{E}(BT_{stoch}) \dots \mathbb{E}(BT_{stoch}^k)$, $\mathbb{E}(TTS_{stoch}) \dots \mathbb{E}(TTS_{stoch}^k)$, $\mathbb{E}(ST_{stoch}) \dots \mathbb{E}(ST_{stoch}^k)$.

Performance evaluation of the large manufacturing system is obtained through evaluation of all System Views and update of Remote Models, through an iterative procedure. The iterative decomposition procedure is a generalization of the algorithm first proposed in Dallery et al. (1988). The main computational steps are:

1. **Evaluation of the System View:** performance evaluation of every System View is obtained through the modeling approach adopted, DES or analytical. The analytical model adopted in this work is based on the two-machine line with continuous approximation of discrete flow proposed in Magnanini and Tolio (2021).
2. **From System View to Remote Model:** once a System View is evaluated, the dynamics at the borders are synthetized by separating sets of deterministic blocking and starvation states, if present, and computing the moments of the transition time distributions. These informations are transferred to the corresponding Remote Models.
3. **From Remote Model to System View:** information contained in the Remote Model is transferred to the System View by including starvation in arrivals to the sub-system and blocking in departures from the sub-system. Moment matching methods are adopted to fit distributions for random variate generation in DES models and Phase-Type distributions for use in analytical Markovian models (Horváth and Telek (2009)).

All the described steps are performed iteratively until conservation of flow is reached within the system, i.e. there is no statistically significant difference among throughput values of the different System Views. After completion of the algorithm the main steady-state performance measure are computed, as system throughput, average buffer level and machine state probabilities.

3 Conclusions and future developments

The advantages of the proposed method include parallelization of modeling activities of different sub-systems and reduction of development effort for the single model, increased portability and maintainability of system models and best matching of sub-system characteristics and modeling approaches. Future work will be devoted to the integration of data-driven performance evaluation approaches in the hybrid modeling framework, analysis of the effect of integrating models with different levels of fidelity and generalization of the methodology for evaluation and optimization of integrated logistics, quality and maintenance problems.

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Session 5

Chair: Tullio TOLIO

Evaluating decomposition error in discrete-time open tandem queues

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We investigate discrete-time open tandem queues with external Poisson arrivals and gamma-distributed service times to analyze the approximation quality of the discrete-time decomposition technique, compared to simulation. Focusing on the relative errors of the expected value of waiting time, we use multiple linear regression and quantile regression models to compute forecasts and confidence intervals for decomposition error. The prediction models are found to provide significant forecasts for the approximation quality. We identify utilization and arrival process variability as the major impact factors on decomposition error.

Key words: Decomposition, Tandem queue, Waiting time, ANOVA

1. Introduction

Queueing models are widely used for performance evaluation of manufacturing and logistics systems which are subject to the influence of randomness (Shanthikumar et al. 2007, Van Nieuwenhuyse and de Koster 2009, Malmborg 2003, Wu et al. 2019, Yu and de Koster 2009, Dong and Chen 2005, Lieckens and Vandaele 2012). When applying continuous-time queueing models, engineers calculate the first and second moment of performance indicators of interest, e.g. throughput, waiting time, and the number of customers in the queue. However, production and logistics systems are typically designed to guarantee performance not on average, but with a given probability (e.g. 95%). Consequently, understanding service performance necessitates the calculation of the distribution of key performance indicators (such as waiting time) to know, for example, which percentage of orders are processed in 3h or less, or what promised throughput time will be met in 95% of the cases (Schleyer and Gue 2012).

The analysis of discrete-time open queueing networks relies on a decomposition approach. As in the continuous-time domain, the technique is known to yield approximate results in the case of non-Poisson arrivals and generally distributed service times. The drawback with approximations is that it is unknown how far the performance measures calculated with a decomposition approach deviate from their actual values. While the approximation quality of decomposition has been studied in the literature for the continuous-time domain (see e.g. Suresh and Whitt (1990) and Kim et al. (2005)), the decomposition error in the discrete-time domain has not yet been comprehensively examined. Therefore, we investigate discrete-time open tandem queues to analyze the approximation quality of the discrete-time decomposition technique, compared to simulation. We identify major influencing factors on the approximation quality of the decomposition approach and determine the conditions under which the approximations are satisfactory. Further, we compute forecasts to predict the expected decomposition error as well as confidence intervals for decomposition error.

2. Theoretical background

In the continuous-time domain, well-known decomposition approaches with respect to generally distributed inter-arrival and service times are proposed, among others, by Shanthikumar and Buzacott (1981), Whitt (1983), and Bitran and Tirupati (1988, 1989). Each decomposition approach relies on two basic assumptions (Govil and Fu 1999): First, it is assumed that the individual queueing systems can be treated as being statistically independent GI/G/1-queues. Second, it is assumed that the point process which forms the input to each GI/G/1-queue can be approximated by a renewal process. Decomposition approaches for discrete-time open queueing networks are based on these conditions, as well. The arrival stream of a downstream queue is approximated as renewal process by the inter-departure time distribution of the upstream queue, which can be efficiently computed with the algorithm by Jain and Grassmann (1988). The waiting time distribution of the resulting GI/G/1-queue is obtained with the algorithm presented by Grassmann and Jain (1989). Further performance measures, such as the distribution of customers, can be computed with the approaches presented by Haßlinger (1995), and Grassmann and Tavakoli (2019). It is well known that the assumption of independence among queueing systems does not properly account for the correlations of the arrival stream which have a significant effect on the performance measures (Kim et al. 2005) and therefore, it is important to emphasize that congestion measures obtained by decomposition techniques are approximate.

In an effort to investigate the approximation quality of the decomposition techniques, tandem lines have been studied extensively in the literature. Suresh and Whitt (1990) examine the impact of non-renewal processes on the approximation quality with different traffic intensities. Wu and McGinnis (2013) introduce the intrinsic ratio, a fundamental property of tandem queues that is based on the insight that some servers are directly affected by the external arrival process. The intrinsic ratio can be exploited to achieve improvements in the approximation errors relative to prior approaches when computing the cycle time. Whitt (1995) suggests using a variability function (instead of a single parameter, as in the QNA) for the arrival stream of the downstream queue, that is a function of the traffic intensity of the incoming queue. Sagron et al. (2015) extend this method to multi-class systems that address the scenario where the upstream server in a tandem queue experiences downtimes (e.g. set-up, maintenance, and repair), events that increase the station's departure variability, while causing starvation of a downstream bottleneck station. To achieve better computational efficiency, Sagron et al. (2017) approximate the between-class effect (the variability caused by interactions with other classes) in a queue with downtimes using a Regression-Based Variability Function (RBVF). RBVF receives the squared coefficient of variation of the arrival and service times, as well as the expected value of the service process as input and approximates the variability function using methods of linear regression, which significantly raises the prediction quality of performance measures, compared to recent decomposition approaches.

3. Methodology

We investigate tandem queues, that is, two discrete-time queueing systems are arranged one after the other. The upstream queueing system is fed by an external arrival stream with arrival rate $1/E(A_u)$ of customers. The service processes B_u and B_d at the upstream and downstream queue are described by discrete gamma distributions. Since the arrival process at the downstream queue is approximated as point process with inter-arrival time distribution A_d, only the downstream queueing system is prone to decomposition error.

We evaluate the error of the waiting time W at the downstream queue computed by the discrete-time decomposition approach, compared to discrete-event simulation. Let $\Delta(E)$ be the relative divergence of the expected value of waiting time

$$\Delta(E) = \frac{E_{Sim}(W) - E_{Queue}(W)}{E_{Sim}(W)}, \tag{1}$$

where $E_{Sim}(W)$ and $E_{Queue}(W)$ denote the expected value of waiting time, computed with the discrete-time queueing approach and simulation, respectively. We use Ordinary Least Square (OLS) multiple linear regression to compute forecasts for $\Delta(E)$, and quantile regression (Koenker and Bassett 1978, Koenker and Hallock 2001) to compute confidence intervals of the forecasts.

4. Results

The empirical cumulative distribution of decomposition error in the data set shows that both, positive (meaning that discrete-time queueing theory underestimates the waiting time) and negative errors (overestimation of the waiting time) are found. We find the relative errors in the range of -21.9% and 32.5% with mean absolute value of decomposition error of 3.93%. The OLS regression analysis is found to be statistically significant ($F(10, 921) = 2123$, $p < .001$), explaining the majority of the variance of the relative error of the expected value of waiting time ($R^2_{Adj.} = 0.958$). The quantile regression models are statistically significant as well, with Pseudo R^2 values well above 0.8. The ANOVA of the regression models reveal all direct effects to be statistically significant.

We identify the service process variability at the upstream queueing system and the arrival process variability at the downstream queueing system, as well as the utilization of the tandem queue as major impact factors. Utilization is the enabler for decomposition error since the waiting time in low traffic queues is found to be computed with high accuracy while severe decomposition errors only occur in heavy traffic systems. The arrival process variability determines the tendency (that is, overestimation or underestimation of the waiting time) of the decomposition technique.

The OLS and quantile regression models are found to provide accurate forecasts of decomposition error as well as precise confidence intervals. With the models computed, we can predict the expected decomposition error for a given tandem queue based on the utilization and variability parameters and provide the statistical confidence of the prediction with the 90%, 95%, and 99% confidence intervals. Moreover, the predictions of the point and interval estimates remain accurate for value ranges of flow parameters outside the parameters defined in our initial design of experiments.

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A Queueing System with Risk-Averse Strategic Customers: Equilibrium Behaviour and Pricing

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We consider an M/M/1 queueing system with strategic customers who take the decisions of whether to join a queueing system or not based on an exponential utility function that trades off the reward from service against the waiting times. For an observable M/M/1 queue, where arriving customers can observe the queue length at arrival instants, we characterize the joining decisions in terms of a threshold based on the queue length at the arrival instant. We investigate how the joining threshold changes as the risk sensitivity degree changes. For the unobservable counterpart, where customers do not have information on the queue length, we characterize the equilibrium joining probabilities and explore how the equilibrium changes as the risk sensitivity increases. We then turn our attention to the pricing problem of the system administrator. We characterize the service price that maximizes the expected revenue of the administrator and explore the impact of risk sensitivity on the optimal price. Finally, we propose a pricing scheme to obtain the socially optimal arrival rate. Our results show that pricing for social optimization with risk-averse customers sometimes yields very different results than with risk-neutral customers.

Key words: Queueing System; Risk-aversion; Strategic Customers

1. Introduction

Consider a queueing system where customers are able to decide whether to balk or join after their evaluation of the queue characteristics. As it is experienced by almost all, in many cases, the waiting time in a queue is random and has a crucial role in a customer's decision upon arrival. One relevant question to be addressed is, how strategic customer decisions would change if the customers are risk-averse? The paper by Naor (1969) is the first to explore the customers' decisions of whether to join a queueing system or not based on the current queue length (which determines the expected wait for the customer). Customers are assumed to be risk-neutral, i.e. they have a linear utility function. In this regard, a large part of the body of literature on strategic queueing systems also assumes that customers are risk neutral. However, the preferences of time-sensitive customers could be sometimes better reflected by nonlinear preferences modeled by a concave utility function rather than a linear one. In our paper, we are interested in exploring how risk-averse strategic customers would make decisions, by supposing that customers' utility function is concave in their pay-off. In particular, we suppose customers possess an exponential utility function to address the nonlinear preferences of customers. Following Naor (1969), the related literature on queues with strategic customers, has grown significantly exploring different types queueing models and information structures. When customers are modeled as strategic decision makers, they must not only react to the service-system properties but also to other customers' decisions since resources are usually shared or consumed simultaneously with other customers in a service system.The book by Hassin and Haviv (2003) presents this modeling and analysis framework in a comprehensive manner. Hassin (2016) provides a classification of the state-of-the art research in this area.

The literature on strategic queueing systems is very rich and continues to evolve starting with Naor (1969). In that paper, a toll is charged on newly arriving customers in an observable M/M/1 queueing system and it is shown that imposing such a strategy might lead to social optimality in many cases. To elaborate, In Naor (1969)'s Model Customers are observing the number of other customers in a single-server queue (known as *an Observable Queue*), and decide whether to join the the queue or balk, based on their expected obtained utility. Customers are assumed to have a risk neutral utility function, valuing service at R and incurring a waiting cost at rate C per unit time. Edelson and Hilderbrand (1975) study a similar M/M/1 queueing system, except that customers are not able to see the number of other customers in the system (known as *an Unobservable Queue*). As it was discussed above, a majority of papers in the strategic queueing literature suppose that customers possess a linear utility function. However, there are a few papers which consider that customers might be risk-sensitive and base their strategic decisions on a nonlinear utility function Afèche et al. (2013), Guo et al. (2011) and Wang and Zhang (2018). Differently from these papers, we model risk-sensitivity by an exponential utility function. We are then able to obtain some explicit results on the effects of risk-sensitivity and explore how decisions depend on the risk-aversion degree. We should note that, in addition to modeling risk-sensitivity, our research also contributes to another stream of literature, namely pricing in service systems.

2. Modeling features

We suppose risk-averse customers are arriving according to a Poisson process with rate Λ and there is a single server, and the service durations are i.i.d exponential random variables with intensity rate μ. The service price is p and identical for all customers. The reward is r for a joining customer and identical for all customers. The waiting cost per unit of time in the system is c. A customer who arrives is able see the number of customers in the queue, n_q. To reflect the risk-averse behavior of customers we would use an exponential utility function. Therefore, the utility obtained by a customer who decides to join is

$$u(r - p - c(X|n_q) = 1 - e^{-\theta(r-p-c(X|n_q))} \tag{1}$$

where, $X|n_q$ denotes the waiting time conditional on the observed queue length n_q, θ represents the risk-aversion degree. The expected utility of an arbitrary Customer who decides to join with risk-sensitivity degree, θ is then $\mathbb{E}[u(r - p - c(X|n_q))]$. Note that, $X|n_q$ is the sum of $n_q + 1$ independent Exponential random Variables with rate μ. As a result, $X|n_q$ follows an Erlang distribution with parameters $(n_q + 1,\ \mu)$. Upon arrival, a customer should decide whether to join or balk. The mentioned customer, in case of pursuing self-interest, makes a decision based on his expected earned utility. The optimal decision can be characterized in terms of a threshold queue length. An arbitrary customer who arrives, observes the queue size, n_q, at that instant and decides to join if it is under a level, n (the so-called threshold). Given the threshold n, the stationary number of observed customers in the system, N_q is a random variable which only takes integer values in the interval $[0, n]$. Now, suppose we are interested in characterizing the customers who are pursuing self-interest, In the sense that, an arbitrary customer would join if $\mathbb{E}[u(X|n_q)] \geq 0$ and balk if $\mathbb{E}[u(X|n_q)] < 0$. Our purpose is to find an expression for the threshold queue length which is optimal under self-optimization. The threshold queue length which also implies self-interest is denoted by n_e. We call n_e the threshold strategy adopted and if an arriving customer observes n_e or more customers he would balk, and for $n_q \leq n_e - 1$ he would join. We prove that the optimal threshold n_e is non-increasing in the risk-aversion degree θ. Then, we extend our results by solving the revenue-maximization problem (both in the static pricing and dynamic pricing cases) and the social welfare maximization problem.

In the unobservable case, the arbitrary arriving customer is unable to see the queue length; and the waiting time, X is the unconditional waiting time. In this case, an arriving customer decides to "join,balk or join with a probability" based on a comparison of his expected earned utility computing X which now depends on the decisions of other customers. If his earned expected utility obtained by deciding to join is greater than his earned utility by balking, u(0), he joins. Otherwise, the customer decides to balk and in case of a tie he decides joining with a positive probability $0 < q < 1$, which is characterized based on the service parameters. Since we suppose all customers possess the same utility function, the Nash-Equilibrium of this game is symmetric. If we suppose that in the equilibrium all customers are joining with probability q, then the effective arrival rate is $\lambda = q\Lambda$. By using the standard approaches in an $M/M/1$ queue, given $\lambda < \mu$, it turns out that the waiting time, X, follows an exponential distribution with rate $\mu - \lambda$, where $\lambda \in [0, \Lambda]$ is the effective rate of the customers joining. Afterwards, we extend our results by characterizing the revenue maximizing price and come up with a pricing scheme to obtain socially optimal arrival rates. It turns out that the pricing scheme for queueing systems with risk-averse customers is quite different than the case with the well-known risk-neutral case.

In conclusion, we present a complete analysis with risk-averse strategic customers in an M/M/1 queue where the customers have an exponential utility function. We are able to present results on how strategic decisions change as the degree of risk aversion changes and also explore the effects of risk-aversion on optimal pricing. Our results indicate that risk-aversion has a significant impact on customer decisions and therefore on the system design.

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Online Re-scheduling in the context of Distributed Maintenance

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Keywords: Distributed Maintenance; Production Systems; Routing Optimization; Emergent Failures; Re-scheduling.

1. INTRODUCTION

Nowadays, manufacturing companies have a wide range of technologies, making them more productive than they have ever experienced [1]. Such efficient production systems require high-cost investment in the initial installation [2]. Thus, one of the main goals of managers is to ensure an optimal operating life span of these manufacturing assets [3]. A large part of activities is to prevent or repair equipment failures through maintenance management [4]. The random nature of failures occurrences is the main difficulty tackled by the researchers. Furthermore, maintenance activities require a budget and resources (spare parts, operators and tools), which are limited. An additional problem, allocation [5], appears when a single company has to maintain various equipment in geographically distributed production sites.

This study focuses on Distributed Maintenance [6]. The aim is to ensure the reliability and availability of geographically-spread production equipment while optimizing maintenance costs. The approach consists in gathering all the resources in a Central Maintenance Workshop (CMW) that repairs defective equipment and schedules the preventive actions [7]. A Mobile Maintenance Workshop (MMW) physically links the CMW and the various dispersed Production Sites (PS). Several papers contribute in the literature to the implementation of Distributed Maintenance. The first step concerns the design and the size of the CMW that provides resources to the MMW. Secondly, it is necessary to determine the optimal location of the CMW and the capacity of the MMW for transportation [8]. The MMW is a fleet of vehicles that leave the CMW with limited spare parts and visit all the PS following an optimal schedule. Once a vehicle reaches a PS, a piece of equipment is replaced systematically by a spare part based on predicted failures.

The existing papers optimize offline the different parameters necessary for Distributed Maintenance. Many PS share one vehicle for preventive maintenance (PM) operations. However, the literature doesn't consider unplanned equipment failures during the online routing. Hence, this paper aims to provide a novel model considering Corrective Maintenance (CM) due to emergent failures of production equipment under a Distributed Maintenance. Thus, in the event of one piece of equipment failure online, the main challenge is to decide whether or not the schedule of a vehicle should be updated and how to modify it without disrupting the PM visits of the other equipment. As a reminder, after the introduction in Section 1, the materials and methods are defined in Section 2. The following section presents the experiments in the oil & gas field.

2. MATERIALS AND METHODS

2.1. General approach

We consider a Distributed Maintenance with N Production Sites (PS). m vehicles are in charge of visiting the PS through a time horizon τ. Each vehicle starts at the Central Maintenance Workshop (CMW) with a limited capacity of spare parts Q. Preventive Maintenance (PM) operations are optimally scheduled and assigned to each vehicle offline. Then, during the online execution of the schedule, the next PM operation to be carried out by vehicle $k \in \{1,2,\ldots,m\}$ is denoted by i_k. Thus i_k is incremented each time a PM operation is finished. Once a vehicle is empty, it returns to the CMW to be supplied.

In the online occurrence of a piece of equipment failure, the objective is to update the routing of the associated vehicle while minimizing the downtime of the defective equipment and the impact on the routing costs. In this case, Corrective Maintenance (CM) consists in replacing the defective equipment with a spare part as soon as possible. The main assumptions can be summarized as follow:

- Each PS has one piece of equipment subject to uncertain failures.
- A piece of equipment starts in "as good as new" condition, and, after a PM or a CM replacement, it returns to "as good as new" condition.
- A PM operation is a deterministic time T_M spent by a vehicle in a PS.
- The travel times between the PS are deterministic and do not change over the scheduling horizon.
- In the event of a failure, the following PM operation of the defective equipment becomes a CM with an associated penalty cost per unit of downtime (C_w).

Figure 1 presents the general process to update the routing of a vehicle. A first model OMCR (Optimized Maintenance and Capacitated Routing) [8], is necessary to obtain offline the schedule, the optimal times to start the PM $\{S_i\}_k$ and the expected waiting times $\{w_i\}_k$*. Online, a monitoring dashboard allows to instantly have the next PM i_k to be conducted, for each vehicle k. And, if an uncertain failure occurs, the following PM of the defective equipment becomes a CM denoted by i'_k ($i'_k \geq i_k$ in the event of failure; 0 otherwise). The time at which the failure occurs is denoted by $T_{i'_k}$ and the real downtime of the defective equipment is $w'_{i'_k}$, as shown in Figure 2.

The novelty of the approach is the Re-Scheduling Model (RSM), which manages the failures by making a trade-off between the downtime of defective equipment, the routing costs and the disruption of the offline schedule. The RSM model will be presented in detail in the next section.

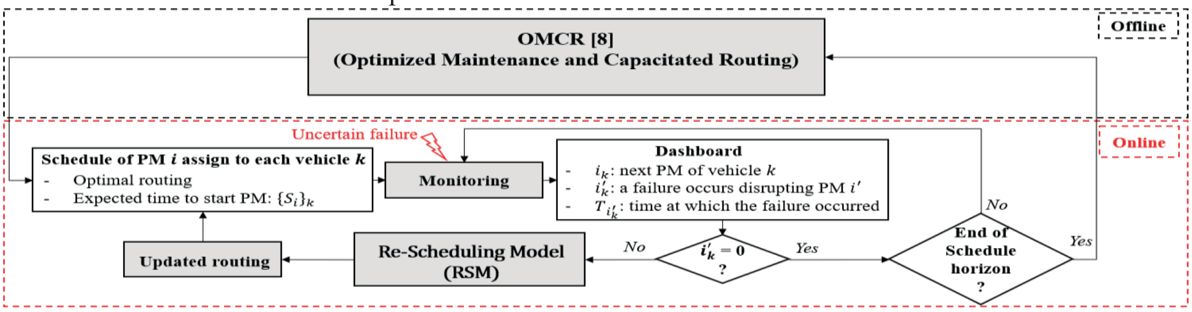

Figure 1. Distributed Maintenance: offline scheduling and online rescheduling

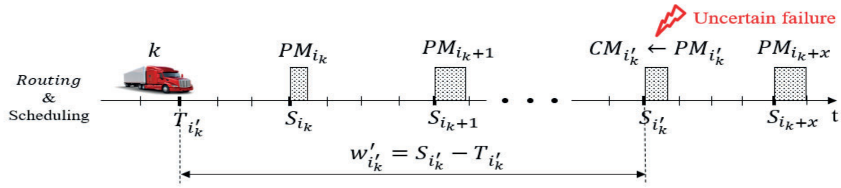

Figure 2. A case of online equipment failure

2.2. Re-Scheduling Model

The RSM is a model inspired by the operators Back-Insert and Swap, which have already proved their performance in Operations Research [9]. It consists in permuting optimally some elements of a given list of tasks, such as the input list and the output one containing the same parts but not in the same order. By

* $\{w_i\}_k$: The periods elapse between predicted failures and the beginning of the next PM operations [8]

adapting these operators, the objective is to ensure that i'_k takes over from i_k if a failure occurs. Then, the affected equipment downtime could be reduced by prioritizing the CM over the other scheduled PM of the vehicle k. Thus, we define two parameters (α, β) to explore when it is profitable to change the schedule of a vehicle. The first parameter α is a ratio which represents the impact in the equipment downtime of the real failure $w'_{i'_k}$ compare to the predicted one $w_{i'_k}$. The higher the α, the earlier the failure must occur than predicted to be considered. The second parameter β is a time which denotes the disruption of the re-schedule in the starting time of the remaining PM operations. The higher the β, the more the differences between the re-schedule PM S'_i $(i = i_k : i'_k)$ and the predicted ones S_i are tolerated.

3. EXPERIMENTS

We implement a case study of 11 PS in oil and gas industry, dispersed in a radius of 300*km.* The production equipment are diverse onshore pumps subject to uncertain failures [10]. The objective is to simulated the vehicles online routing following the proposed model. We choose the software Arena to run the simulation since it is adapted to discrete event studies. 200 replications have been carried out for each scenario to ensure a 95% confidence interval. We perform the experiments on Windows 8, 64 bits personal computer, with an Intel(R) Core (TM) i7-10850H, CPU 2.70 GHz and 32 Go of RAM. Different values of α *and* β are tested to explore the influence on the costs. The results show a profit of more than 420*\$/hour* by prioritizing the CM over the PM operations under optimal defined conditions.

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Session 6

Chair: Raik STOLLETZ

Dynamic Energy Storage with EV Aggregators

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This paper aims at modeling the stochastic behavior of Electric Vehicle (EV) aggregators as an energy storage system with dynamic capacity. An EV lot follows a Modular Energy Storage Architecture where the energy modules are EVs, and each EV space is equipped with a V2G unit. The stochastic behavior of the aggregated storage as a system is driven by random arrivals and departures of vehicles, state of charge (SoC) of vehicles at arrivals and departures, and whether a vehicle is willing to participate. For market participation as an aggregator, we develop a day-ahead plan which takes into account vehicle queues at different times, and a stochastic optimization model aiming at maximizing the lot owner's revenue, constrained by vehicle owner's compensation agreement. A second stochastic optimization model controls charge and discharge of each vehicle constrained by the SoC at times of arrival and departures. The models are demonstrated for an example lot with 120 charging stations. It is shown that participation as an aggregator can reduce the peak demand of the facility by almost 40% which may result in transmission and distribution upgrade deferral in the utility future planning.

The recent advances in battery-related technologies and the reduced price of Electric Vehicle (EV) are markedly changing the landscape of roadway transportation, and more than ever before, the nexus between transportation and energy becomes evident. With the increasing number of EVs on the roadways and the flexibility to charge at home, or at public and private facilities, the demand increases and load uncertainty widens. Besides, the recent advances in Vehicle to Grid (V2G) technology and the lowering cost of bi-directional charging units bring new investment opportunities, especially in the emerging energy storage market. V2G technology and FERC order 841 allow large facilities, such as EV parking lots, to participate in the wholesale energy and ancillary service markets. Thus, EV aggregators have great potentials for tangible financial incentives, especially, in legacy settings such as parking lots where many vehicles can participate at any one time.

An EV lot follows a Modular Energy Storage Architecture (MESA[1]) where the energy modules are EVs, and each EV space is equipped with a V2G unit. The total storage capacity and system configuration are stochastically varying over time due to module *availability* and other governing conditions complicating the behavior of energy storage system (ESS) that a parking lot is a member of. In a typical parking facility, vehicles arrive and depart stochastically, and in case of EVs, the State of Charge (SoC) for these vehicles would be random at the time of arrival. Furthermore, EV owners define the SoC for their vehicles at the time of departure, and the facility owner must pay penalties to them if the time of departure SoC is not met. The *participation* (connect/disconnect) *protocol* is driven by economic benefits and risk constraints where an EV owner permission for V2G depends on the incentive offered by the parking operator and the owner's level of risk-averseness. Thus, not every parked EV is a participating energy storage module making the

[1] MESA is an open set of specifications and standards to accelerate interoperability, scalability, safety, quality, availability, and affordability in energy storage systems.

overall capacity of the ESS stochastic and dynamic as perceived by the distribution network that is serving. These factors together translate to market risks if the aggregator engages in arbitrage or other services.

In the above context, this paper provides insight into stochastic behavior of an EV aggregator as an ESS with dynamic capacity and develops models for its optimal day-ahead planning and operational control in lieu of the underlying risks and financial incentives for EV and facility owners. There are multiple facets to this problem: The facility owner aims at maximizing his/her revenue by optimally controlling bi-directional power flow in the facility, constrained by vehicle owners' permissions. A vehicle owner's decision is partially dependent on what s/he receives in return, either as a discount for the use of the facility or as an expedited payback. The vehicle owner needs to weigh this return against battery degradation. On the other hand, for the owner to participate in the wholesale energy and ancillary service markets, the facility must plan in day-ahead depending on vehicle queues.

A queueing model is developed that explains vehicle arrivals and departures, and the number of vehicles in the facility. The results from this model are fed into a day-ahead planning model which also takes into account day-ahead and regulation market capacity and performance clearing. The day-ahead model assumes optimal operational control for each of the multiple scenarios that are generated according to the stochastic inputs. We also formulate planning risks and risks to the distribution network due to the underlying stochasticity of the facility. The optimal operational control model governs bi-direction power flow in the facility and works closely with the facility and vehicle owner's revenue model. Figure 1 illustrates the holistic view of the proposed approach.

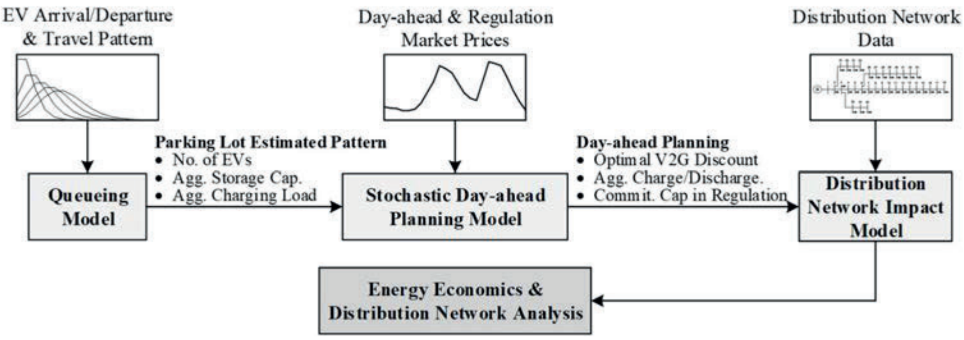

Fig. 1. Schematic diagram of the model

From a queueing point of view, this EV lot works as a G/G/K/ queue, where the two G's are general distribution designations for inter-arrival time and time-to-stay of vehicles, respectively. K is the number of parking spaces and the capacity of the facility. To estimate potential market benefits, an economic dispatch model is developed under the PJM fast regulation market (RegD) rules. The facility owner commits the maximum capacity in peak-priced hours while ensuring that sufficient capacity is available to provide both regulations up/down (discharging/charging) services. For demonstration purposes, we use 2016 PJM day-ahead regulation market data for capacity and performance clearing prices. For the wholesale arbitrage, the facility owner may charge EV batteries when the electricity price is low and sell it back to the grid when the price is high, while the EV SoC demands are met. FR capacity commitment and net injected power, i.e. aggregate charge minus aggregate discharge, must be considered in the day-ahead planning which is scheduled based on EV queueing data, types of batteries, initial and final desired SoC of batteries. Moreover, market variables such as electricity price and FR credit could influence planning. These input variables are stochastic, hence stochastic optimization is applied. The outputs of the model are optimal discount factor assigned to EVs (for V2G permission), aggregated planned capacity for FR commitment (at each time step), aggregated amount of electricity required to charge EVs, and aggregated amount of discharged electricity during each time step. To capture the stochasticity of input variables, a Monte-Carlo (MC) simulation was implemented to generate sample paths according to the stochastic input distributions, one of which is vehicle arrival process characterized by the queueing model.

In conclusion, the paper provides an integrated framework, which aims at maximizing an EV lot benefits by optimally planning for the charge/discharge of EVs that use the lot. The benefit of the EV owners was considered through reduced parking fees or discounted charging fees, which compensates the additional degradation of the vehicle battery. The results quantify the impacts of such facility on the power distribution network approximately reducing peak load by 40% for a commercial lot example with V2G-enabled charging stations. This reduces the power loss in the distribution network and defers the needs for the T&D capacity upgrades. The analysis shows that, with the current state of arbitrage and regulation market, commercial lots can be more beneficial for a parking operator compared to the residential lots, which are only occupied during night times. This happens due to the high FR market clearing price during noon times which coincide with peak-hours of commercial lots. Finally, the analysis of daily EV parking lot revenue shows that the FR credit and electricity prices have an impact on its daily value. It was observed that FR credit has the most impact on the evaluation process.

Structuring Research Activities on Transformative Technologies for Industry 4.0

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The talk will discuss what research methodologies and support may be used to tackle the topic of introducing industry 4.0 technologies in the industry. The presentation will be based on the description of the research platforms and programs recently developed in Grenoble, especially the Operations Management (OM) platform. The OM platform aims at reproducing the manufacturing environment in the laboratory to obtain a means to conduct realistic emulation of industrial cases. The ambition is to be able to realize supervised simulations of industrial cases representative of real systems. In this supervised environment, the issue of performance measurement of I4.0 technologies is renewed by offering solutions to verify the repeatability of obtained results and by permitting to address a multidimensional study of the production system performance. The talk will also address a research program structuring the initiatives on the use of AI techniques for industrial engineering topics. Its use of the OM platform will be detailed, namely discussing the data qualification or availability problems in nowadays industry.

Session 7

Chair: Guido GUIZZI

A newsvendor approach to production planning with stochastic and non-stationary yield

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Key words: Newsvendor; Semiconductor industry; non-stationary yield

1. Introduction

Our research is motivated by the planning problem of a global manufacturer of semiconductors. During the introduction of a new product or machine, the yield of a production process tends to start low and increases with cumulated production. This is known as the ramp-up phase. Yield problems occur when some of the produced products do not meet the quality specifications and can therefore not be used to fulfill the demand. We analyze real yield data from a semiconductor manufacturer. The analysis shows that such a stochastic and non-stationary yield behavior occurs both for the introduction of new products as well as for the introduction of new machines.

There is a separation in planning between the ramp-up phase and the steady-state phase. We analyze the situation, in which the company plans the start of a new product or a new machine. The expected yield during the ramp-up is non-stationary and follows a learning curve. The considered company operates in a business-to-business setting and produces customer-specific products. Therefore, the contracted demand can be considered to be known in advance. Production lead times are long, sometimes up to several months, forcing the company to decide on the ramp-up quantity before the realization of the stochastic yield is known. Even though the company may produce in lots, lot sizes can vary and the decision is on the number of products (chips) to be produced. Therefore, there is a single production decision with a stochastic quantity of resulting non-defective end products to meet a known demand. In case of a supply shortage, the company loses revenue and faces contracted shortfall costs. In case of overproduction, the overproduced units can be sold at a lower value in the steady-state phase. This lower value represents both the decreasing prices in the high-tech industry as well as inventory holding costs. The company aims to maximize its expected profit.

In this work we analyze empirical yield data, formalize the optimization problem and provide analytical and numerical insights on optimal decisions and the resulting profit.

2. Yield Data Analysis

We were provided with data by a global manufacturer of semiconductors. We describe and analyze data for the introduction of new products and new machines. The new machines are spread over the entire process of semiconductor manufacturing and their realized yield is measured directly at the machine. In contrast, the yield of the new products is always measured at the end of the wafer probe area. We have two data sets, each spanning approximately three years of production.

The data originates from the production process of wafers, which are thin slices used in semiconductor manufacturing, where each wafer consists of a large number of microchips. The manufacturer produces its microchips in lots, where each lot is a batch of wafers. The data consists of the average realized yield for each lot. Each data point represents a single processing step of a single lot in the production process. As the production quantity per lot is not fixed, we consider the realized average yield in relation to the cumulative production quantity.

In the data for new product introduction and new machine introductions, (1) deterministic and stationary yield, (2) stochastic and stationary yield, as well as (3) stochastic and non-stationary yield can be observed. To further analyze the examples of ramp-ups with stochastic and non-stationary yield, we fit learning curves from the literature to the data. We analyze if the learning curves can be used to model the behavior of the non-stationary yield. The fitted learning curves have values of R^2 between 0.11 and 0.56. In general, the resulting coefficients of determination R^2 are higher for the fitted learning curves of the new product introductions. There is no substantial difference between the fit of the exponential and the hyperbolic yield curve. However, the developed model we present in the succeeding section does not rely on a specific assumption on the learning curve.

While the literature has focused on models with stochastic and stationary yield, non-stationary yield behavior can be observed in the data. Therefore, there is a practical need for a model to capture the non-stationary behavior of the stochastic yield during the ramp-up of a new product or a new machine. Thus, the model we present in the succeeding section features stochastic and non-stationary yield. However, stochastic and stationary yield can also be captured as a special case. Therefore, the model allows to gain insights into both presented classes of stochastic yield.

3. Model

We formalize the company's problem as a Newsvendor problem with stochastic and non-stationary yield. The demand is known and the corresponding ramp-up quantity has to be chosen to maximize the expected profit. Yield is stochastic and the probability of each unit being non-defective follows a learning curve. We assume that the learning curve is known but do not make specific assumptions about its shape. The resulting quantity of non-defective end products is modeled as a Poisson Binomial distribution. Revenue is incurred for the share of the demand that can be fulfilled by non-defective end products. Costs are composed of variable production costs and penalty costs for demand shortfalls. Non-defective end products exceeding the demand can be sold at a salvage value at the end of the ramp-up phase. Choi et al. (2019) have analyzed the special case of stationary yield, i.e. the probability of each unit being non-defective does not change with the production quantity, and no salvage value.

4. Contributions and Key Findings

Our research is motivated by an application in the semiconductor industry, but not limited to it. Rather, it applies to any production setting with stochastic and non-stationary yield and a single decision on the production quantity. We analyze the structure of the optimal ramp-up quantity with non-stationary yield. The main contributions are summarized as follows.

1. We present a Newsvendor model with stochastic and non-stationary yield dependent on the production quantity.
2. We derive analytical insights on the expected profit and the optimal ramp-up quantity. We establish a bound on the optimal ramp-up quantity and the expected profit for any learning curve. For increasing yield, we show that a positive production quantity below the demand is never optimal. For stationary yield, we characterize the optimal ramp-up quantity by a critical fractile and show the sensitivity of a change in the model parameters on the optimal ramp-up quantity. We derive the impact of a change in the cost parameters on the expected profit.
3. A numerical study compares our model with the ex-post optimal decision derived from the data. We find that the optimal ramp-up quantity from the model is close to the optimal ex-post quantity. Furthermore, our numerical study suggests that the monotony of the optimal ramp-up quantity in several model parameters extends to the case of increasing yield. Finally, our numerical study shows that an increase in the expected yield can first lead to more production before it leads to less production, i.e. the optimal production quantity is non-monotone in the expected yield. We observed this non-monotone effect for different examples where the expected revenue per unit for the final yield is close to the production cost per unit. Therefore, this behavior may occur in competitive markets, where marginal revenue is close to marginal cost.

5. Future Research

We assume deterministic demand and a fixed revenue per unit. Future research could analyze the impact of stochastic demand or of allowing the company to set the revenue per unit after the realization of the yield is known. In addition, we assume that each chip is either defective or non-defective and that the probability of each is independent of the realization of previous chips. In some production situations, an error in the production process might lead to an entire wafer being destroyed. Therefore, future research could analyze the impact of different assumptions on the distribution of the non-stationary yield. Furthermore, we assume that the learning curve is known from the previous ramp-up of a similar machine or product. Future research could develop approaches that integrate the prediction of the learning curve.

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A newsvendor based simulation-optimization model with supply disruption, backup reservation, and deterministic demand

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We study the optimal reserved capacity from a reliable backup supplier to hedge against the risks of capacity disruption in main suppliers. The buyer orders from its main suppliers for a single product. An order allocation mathematical model is developed to obtain the optimal order quantities. The objective function is to minimize purchase costs based on the captured performance of suppliers in past periods. Suppliers are subject to random capacity disruption and the risk-averse buyer reserves capacity from one reliable supplier to absorb the shocks. A newsvendor model is added to find the optimal reserve capacity from the backup supplier. Subsequently, each period is divided into sub-periods to stimulate random disruption in main suppliers. It captures the unmet demand due to the under-optimal reservation of backup capacity which affects the optimal capacity that should be reserved in the next periods. The model is programmed in Python which calls a Gurobi optimization model in the outer layer and connects these decisions to a simulation model of disruption in the inner layer. Results show that the proposed optimization-simulation newsvendor model reduces unnecessary reservations and obtains higher profit compared to the classic newsvendor model with a fixed reserve capacity.

Keywords: Supply disruption; Backup capacity reservation; Newsvendor model; Service level

1 Introduction

Due to the significant consequences of supply disruption on global business, there is a growing concern about the availability of suppliers during global crises (Hamdi et al. (2016)). According to Papachristos and Pandelis (2022), supply uncertainty may be caused by varying resource availability as a result of unexpected disruption and unplanned issues. An example from Renesas, a leading automotive microcontroller and semiconductor manufacturer, suffered seriously at its semiconductor plants after the Japanese earthquake and tsunami in 2011 that caused months of delays in global auto manufacturing supply chains (Yamazaki and Saoshiro, (2015)). As another example, a dispute between Volkswagen and its suppliers in 2016 led to a production stop in six of the carmakers' German factories (Katsaliaki et al. (2020)). For examples of suppliers with uncertain capacity, Banker (2019) discussed offshore plants for Brexit that are often with low reliability and capacity disruption risks at the EU-UK borders which could lead to late deliveries and logistics failure.

Firms in the modern economy embrace a variety of supply-risk mitigation strategies to improve the reliability of suppliers (Chang and Lin (2019)). Companies acquire proactive strategies like contingency strategies to hedge against supply disruption risks. Backup sourcing, and more specifically the capacity reservation from a reliable backup supplier, which is the topic of this study, is a particular type of contingency strategy to pay non-refundable fees to reserve capacity from a reliable supplier. It enables delivery from the backup supplier up to the reserved quantity after a disruption in main suppliers. According to Xu et al. (2017) and the references therein, approximately 15% of EU customers accept the backorder when stockouts occur.

Capacity reservation policies and contracts are widely addressed in related literature (Li and Zhou (2019); Cheaitou and Cheaytou (2019); Li et al. (2021)). Hou et al. (2017) developed a backup sourcing strategy with a capacity reservation policy under disruption risk. Erkoc and Wu (2005) studied capacity reservation contracts between a manufacturer and a buyer. The buyer reserves capacity by paying a deductible reservation fee in advance. More close to this study, Zeng and Xia (2015) described Staples and GE Aviation as examples of firms that contract with a reliable supplier for capacity reserve that is deliverable in the case of supply disruption in the main suppliers. We analyze the model of a buyer that orders from its main suppliers with random supply capacity. The contribution of this paper lies in the implementation of a newsvendor model embedded in an optimization-simulation model capable of dynamic monitoring of shortages. Comparing the optimal quantity of the newsvendor model with the monitored shortages in the previous period, the minimum value is selected as the lower bound of capacity reservation from the backup supplier to avoid redundant reservations. The proposed mathematical model optimizes the quantity of reserved capacity at each period and minimizes the risks associated with ordering from main suppliers with poor reliability. See (Ghiami and Beullens (2016); Xu et al. (2017); Chakraborty et al. (2020)) to analyze the application of the newsvendor model with a backup supply strategy in related literature. The remainder of this extended abstract is organized as follows. Section 2 describes the problem and proposed mathematical model. A numerical experiment is described in Section 3 followed by the conclusions.

2 Problem Description

We address a single-period model with a buyer facing deterministic demand (D). The buyer orders from its main suppliers $(i = 1,2,3, \dots, N)$ at the beginning of each period $(k = 1,2,3, \dots, K)$ up to their available capacity. The term service level (Z_i) is used in this paper to show the available capacity of suppliers as a fraction of the maximum supply capacity (Cap_i). To hedge against supply disruption, the buyer pays a non-refundable fee (C_r) to reserve capacity from one reliable backup supplier whose capacity could be used in the case of supply disruption. Any unmet demand due to under-reservation causes penalty costs (C_{ud}). We assume that suppliers are subject to random disruption and shortage in main suppliers is a uniform continuous random variable with probability density functions f and cumulative distribution function (F). At the beginning of each period, the buyer should place an optimal order of (S_i) from its main suppliers and the optimal capacity reserved from the backup supplier (BR). Each period is subsequently divided into sub-periods to simulate supply disruption and calculate shortages. The buyer can meet shortages up to the reserved capacity in purchase costs of (C_b). After the delivery of orders by both suppliers, the buyer sells as much as possible at a price (r) per unit of product. By the end of each period, the buyer evaluates the performance of suppliers and the mean amount of shortages for a more precise order allocation and capacity reservation in the next periods.

2.1 Model Formulation

The proposed order allocation model seeks to reduce the risks of ordering from disrupted suppliers while optimizing the capacity reserved from the backup supplier. The proposed mathematical model is as follows:

$$Min\ Z_{[k]}: \sum_{i=1}^{N} (S_{(i,k)} \times [C_i + (P_{(i,(0,(k-1))} \times [(w_{[k-1]} \times C_b) + ((1 - w_{[k-1]}) \times C_{ud})])]) + (BR_{[k]} \times C_r)$$

Subject to the following constraints:

$$\textstyle\sum_{i=1}^{N} S_{(i,k)} \geq\ D + (I_0 - I_{(remain,(k-1))}) \tag{1}$$

$$S_{(i,k)} \leq \left(Z_{(i,k)} \times Cap_{(i,k)}\right) \qquad \forall\ i = 1,2, \dots, N \tag{2}$$

$$S_{(i,k)} \geq \left(Z_{(i,k)} \times Cap_{(i,k)}\right) \times \eta \qquad \forall\ i = 1,2, \dots, N \tag{3}$$

$$BR_{[k]} \geq min\left(F^{-1}\left(\frac{r+C_{ud}-C_r-C_b}{r+C_{ud}-C_b}\right), SH_{[k-1]}\right) \tag{4}$$

$$S_{(i,k)}\ and\ BR_{[k]} \geq 0 \tag{5}$$

in which I_0 is the maximum safety stock for the buyer for small fluctuation and $I_{(remain,(k-1))}$ states the remaining quantity of safety stock from the previous period. Constraint 1 formulates the supply-demand balance at each period. Constraints (2) and (3) define the upper and lower bounds for optimum order concerning the supply service level, respectively. The term $F^{-1}\left(\frac{r+C_{ud}-C_r-C_b}{r+C_{ud}-C_b}\right)$ in constraint (4) calculates the optimal reserved capacity based on the newsvendor model. It is worth mentioning that the optimal ordering level of the newsvendor model is determined by $\left(\frac{Loss_u}{Loss_u+Loss_o}\right)$, where $Loss_u$ expresses the losses due to under-optimal reservation and $Loss_u$ indicates the losses due to over-optimal reservation from the backup supplier (Xu et al. (2017). Accordingly, we will have $Loss_u = r + C_{ud} - C_r - C_b$ and $Loss_o = C_r$. The term $SH_{[k-1]}$ in constraint (4) denotes the number of shortages observed during the simulation of disruption in the previous period. $P_{(i,(0,(k-1))}$ in the objective function states the contribution percentage of supplier i to the cumulative shortages in a period of [0,(k-1)] in which $w_{[k-1]}$% of shortages is met using backup reservation policy and $(1-w_{[k-1]})$ % has remained as unmet demand.

3 Numerical experiments and conclusions

Given the values r=55, C_i=30, C_b=40, C_r=4, and C_{ud}=4 from Papachristos and Pandelis (2022) and D=2000 units of product for a period of 52 weeks (1 year), the model is run for three main supplies. For the simulated disruption in suppliers shown in Figure 1 (A), the proposed model is compared with the classic model excluding $SH_{[k-1]}$ in constraint (4) and the captured performance of suppliers in the objective function. Figure 1 (B) compares these two models in terms of the reserved capacity.

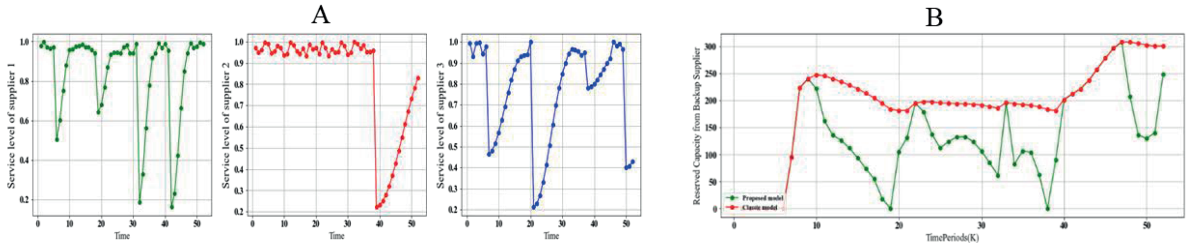

Figure 1. Reserved capacity in the proposed model compared with the classic model (B) for the given disruption (A)

As shown, the proposed optimization-simulation newsvendor model reduces unnecessary reservations. While smaller quantity of backup reservation may put in doubt the performance of proposed model, results show that the proposed model obtains in average a higher profit and lower shortages compared to the classic model. It highlights the importance of dynamic analysis for order allocation under uncertainty.

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Session 8

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Continuous-flow simulation of manufacturing systems

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In this work, a continuous-flow simulation of manufacturing systems with linear and nonlinear material flows, loops and assembly/disassembly machines is provided. The types of systems discussed in this paper are highly automated systems with unreliable machines and intermediate buffers. Machines can have multiple up and multiple down states, with deterministic production rates in the operational states and stochastic failures and repairs. The continuous-flow simulation model is presented in a wider framework for the performance evaluation of manufacturing systems. The framework is composed by three modules. The first module is a propagation analysis of any material flow interruption in the manufacturing system. The second module is the actual simulation model of the system. In this simulation model, the discrete nature of the material flow in the system is approximated by a continuous-flow. The advantage provided by the continuous-flow approximation is to reduce the number of discrete events occurring during a simulation run and so to significantly improve the computational time of the simulation. The third module of the framework consists of in-depth analyses of the system behaviour, such as the definition of the probability distribution of the buffers' level and of the flow time in the system.

Keywords: performance analysis; simulation; continuous material flow

1 Introduction and general notations

In this work, a performance evaluation framework of manufacturing systems based on a continuous-flow simulation model is presented. Analytical models based on a continuous flow of material have been extensively employed for the evaluation of unreliable production system (Dallery and Gershwin, 1992) (Papadopoulos et al., 2019), especially for asynchronous machines. When systems cannot be modelled as Markovian processes, discrete event simulation (DES) is used. In DES models each unitary increase and decrease of the buffer levels is modelled as a discrete event, although it may not affect the material flow in the system. When machines have deterministic processing times, the computational performance of the simulation can be significantly improved by considering only the events that change the flow rates of the machines, such as machine failures and repairs, and buffer fulfilments and depletions. By approximating the discrete flow of parts with a continuous material flow, the clock time is instantaneously advanced from an event time to the next one affecting the material flow, and the changes of buffer levels in the time period are calculated from the flow rates of the machines. The ambition of this work is to generalize the continuous-flow simulation proposed in Tan (2015) and in Hosseini et al. (2017) to production systems with general layout and with operation dependent failures. The manufacturing system of interest is a general network with M unreliable machines and B finite buffers. Machines can perform assembly and disassembly operations, and loops of material flows are allowed in the system. Each machine is represented by the notation $M\{m\}$, with $m = 1, \dots, M$, and the behaviour of each machine in isolation can be described by a vector of states $\dot{S}\{m\}$ of size $I\{m\}$. In each state $S_i\{m\} \in \dot{S}\{m\}$, the machine $M\{m\}$ processes parts with a nominal production rate $\mu_i\{m\}$, with $\mu_i\{m\} > 0$ for the up states and $\mu_i\{m\} = 0$ for the down states. The time to transition between two states $S_i\{m\}$ and $S_j\{m\}$ is a stochastic variable with continuous probability distribution $D_{i,j}\{m\}$. Therefore, the times to transition between the states of each machine in isolation can be described by the probability distribution matrix $D\{m\} = [D_{i,j}\{m\}]$. Each buffer of the system is represented by the notation $B\{b\}$ with $b = 1, \dots, B$, and it has a finite or infinite capacity, defined between a lower boundary $L\{b\}$ and an upper boundary $N\{b\}$. The flow of parts from a machine to a buffer and vice versa is define by the flow matrix F, with B rows for the buffers and M columns for the machines. If $F_{b,m} = 1$, it means that the machine $M\{m\}$ feeds the buffer $B\{b\}$. If $F_{b,m} = -1$, it means that the machine $M\{m\}$ is fed by the buffer $B\{b\}$.

2 Performance evaluation framework

In the following, the framework for the performance evaluation of manufacturing systems by means of continuous-flow simulation is introduced. The framework is composed by three main modules: the propagation analysis of flow interruptions; the continuous-flow simulation; the in-depth analyses of the system behaviour. Each module of the framework is fed by specific inputs, and it provides specific outputs which can be both results for the user and inputs for the next module.

2.1 Propagation analysis of flow interruption

The first module is an analysis of the propagations in the system of any interruption of the material flow. This module is performed before running the simulation of the manufacturing system. The aim of this analysis is to identify all the possible sequences of machines and buffers which can theoretically propagate a flow interruption from any machine $M\{m'\}$ to any other machine $M\{m\}$. The only input required by this module is the layout of the system, which is formalized in the flow matrix F. The flow interruption paths identified in this module for each machine are then used in the next module, the continuous-flow simulation.

The first step of this analysis is the representation of the system layout as an undirected graph $G = (V, E)$, in which both machines and buffers are the vertices $V = \{M\{1\}, \dots, M\{M\}, B\{1\}, \dots, B\{B\}\}$, while material flows between machines and buffers are the edges of the graph $E = \{e_1, \dots, e_n, \dots, e_N\}$, such as for each non-zero element $F_{b,m}$ of the flow matrix F an edge $e_n = \{M\{m\}, B\{b\}\}$ in E is defined. Then, an external vertex $M\{0\}$ is added to the set V, and each vertex in V corresponding to a machine in the system is connected through an edge to the external vertex $M\{0\}$. To identify all the possible propagations of any flow interruption in the system which can reach a specific machine $M\{m\}$, depth first search (DFS) algorithm (Jungnickel, 2008) is implemented, with $M\{0\}$ as starting vertex. Each time the vertex of the machine $M\{m\}$ under analysis is reached in the algorithm, the sequence of vertices in the path from $M\{0\}$ to $M\{m\}$ is added to set of flow interruption propagations which can reach the machine $M\{m\}$. For each identified path, the critical levels of the buffers in the path that allow the propagation of the flow interruption are defined: if a buffer $B\{b\}$ is crossed in the path in the same verse in which the material flows through $B\{b\}$ in the system, the flow interruption propagation corresponds to a starvation propagation and the critical level corresponds to the minimum level $L\{b\}$ of the buffer (e.g., buffer empty); if $B\{b\}$ is crossed in the path in the opposite verse of the material flow, it corresponds to a blocking propagation and the critical level is the maximum buffer capacity $N\{b\}$. By performing DFS for each machine, all the possible starvation and blocking propagations which can affect the material flow of any machine in the system are identified.

2.2 Continuous-flow simulation

The second module is the continuous-flow simulation model of the manufacturing system. In this simulation, the discrete flow of parts in a manufacturing system is approximated with a continuous material flow. The inputs of this module are the system parameters and layout defined in section 1, the propagation paths defined in the previous module, the simulation time T and the initial values of the variables below describing the system.

At any event time t_k of the simulation, the state of the system is described by the buffer level $x(b, t_k)$ of each buffer $B\{b\}$ and by the following machine variables:

- the current state $s(m, t_k) = S_i\{m\}$ of each machine $M\{m\}$;
- the $RT(m, t_k)$ matrix of size $I\{m\} \times I\{m\}$, defining the residual times before the occurrence of a transition between any couple of states of a machine $M\{m\}$;
- the current flow rate $\mu(m, t_k)$ of each machine $M\{m\}$. It can be equal to the nominal production rate of the current state, or it can be different if at time t_k the machine is slowed down, blocked or starved;

From this system condition at time t_k, the time period Δt_k after which the next event changing the material flow anywhere in the system will occur, must be defined. To compute Δt_k, it is necessary: to find for each machine the minimum residual time in the ith row of the matrix $RT(m, t_k)$, corresponding to the current state $s(m, t_k)$ of the machine; to compute the time to fulfil or to deplete each buffer; to find the minimum value among all these times above. If at t_k the upstream machine $M\{m\}$ of the buffer $B\{b\}$ is faster than the downstream machine $M\{m'\}$, the time to fulfil the buffer is computed as $\frac{N\{m\}-x(b,t_k)}{\mu(m,t_k)-\mu(m',t_k)}$. If $M\{m\}$ is slower than $M\{m'\}$, the time to deplete the buffer is computed as $\frac{|L\{m\}-x(b,t_k)|}{|\mu(m,t_k)-\mu(m',t_k)|}$. If $M\{m\}$ and $M\{m'\}$ have the same flow rate, both fulfilment and depletion times are set equal to $+\infty$.

After the computation of Δt_k, the clock time of the simulation is advanced to $t_{k+1} = t_k + \Delta t_k$ and the variables describing the system are updated as follow. If the event at time t_{k+1} is a transition to another state $S_j\{m\}$ of the machine $M\{m\}$, the current machine state is updated as $s(m, t_{k+1}) = S_j\{m\}$, otherwise $s(m, t_{k+1}) = s(m, t_k)$. The residual time matrix of each machine is set $RT(m, t_{k+1}) = RT(m, t_k)$. Then, the ith row in $RT(m, t_{k+1})$ corresponding to the old state $s(m, t_k)$ is reduced by a quantity proportional to the time interval Δt_k, and if any element $RT_{i,j}(m, t_{k+1})$ results equal to 0, a new random value is generated according to the distribution $D_{i,j}\{m\}$. The level of each buffer $B\{b\}$ is updated as $x(b, t_{k+1}) = x(b, t_k) + \Delta t_k \cdot \big(\mu(m, t_k) - \mu(m', t_k)\big)$, with $M\{m\}$ and $M\{m'\}$ the upstream and downstream machines of $B\{b\}$. The current flow rate $\mu(m, t_{k+1})$ of each machine $M\{m\}$ is then updated as the minimum value between the nominal production rate of $M\{m\}$ in its new state $s(m, t_{k+1})$, and the nominal production rates of all the machines which can affect the material flow in $M\{m\}$ at the time t_{k+1}. At time t_{k+1}, $M\{m\}$ can be limited by all the machines $M\{m'\}$ for which a propagation path from $M\{m'\}$ to $M\{m\}$ exists, and for which all the buffers $B\{b\}$ in the path have current levels $x(b, t_k)$ equal to their critical levels.

The computation of the next time period Δt_{k+1} and the update of all the system variables are iteratively performed until the achievement of the simulation time T. The output of the continuous-flow simulation model is the event log, from which the main aggregated performance such as the system throughput, the average buffer levels and the machine state probabilities can be easily computed.

2.3 In-depth analyses of the system behaviour

The third module is composed by two different and independent analyses, which are performed to extract from the event log of the continuous-flow simulation the following results: the response surface of the joint probability distribution of the levels of any couple of buffers in the system; the probability distribution of the flow time through any system portion of interest.

To compute the response surface of the buffer level joint distribution, the continuous and bidimensional space $(x_b, x_{b'})$ defined by the joint levels of any two buffers $B\{b\}$ and $B\{b'\}$ is discretized in subspaces with arbitrary discretization units, and the probability of each subspace is computed as the time spent in the subspace by the trajectory of the joint levels of $B\{b\}$ and $B\{b'\}$ in the event log of the simulation, divided by the simulation time T. The construction of this response surface is a powerful decision-support tool since it provides the visualization of the correlation between buffer levels, which is one of the key factors affecting the performance of a manufacturing system.

To compute the probability distribution of the flow time from a machine $M\{m\}$ to a machine $M\{m'\}$ in a continuous-flow simulation, the material flow must be discretized in arbitrary and constant discrete quantities Δq. The flow time of the discrete quantity Δq, from $M\{m\}$ to $M\{m'\}$, when the cumulative production of $M\{m\}$ is Q_i, can be computed as $FT(\Delta q, M\{m\}, M\{m'\}, Q_i) = t_{k'} - t_k$, with $t_{k'}$ the time at which the cumulative production of the machine $M\{m'\}$ is equal to the quantity $Q_i + \Delta q$, and t_k the time at which the machine $M\{m\}$ is operational and its cumulative production is equal to Q_i. The times t_k and $t_{k'}$ are obtained by interpolating the times in the event log of the simulation. By computing $FT(\Delta q, M\{m\}, M\{m'\}, Q_i)$ for Q_i equal to any multiple of Δq that is lower than the overall cumulative production $Q(m', T)$ of the machine $M\{m'\}$ in the simulation time T, the probability distribution of the flow time $FT(\Delta q, M\{m\}, M\{m'\})$ can eventually be defined.

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Performance Analysis and Capacity Planning of Multi-Stage Stochastic Order Fulfilment Systems with Levelled Order Release and Order Deadlines

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Order fulfilment systems are forced to efficiently manage a highly volatile customer demand while simultaneously meeting customer-required short order deadlines. To cope with these challenges, we present the *Strategy of Levelled Order Release (LOR)* for workload balancing over time on a tactical level. We introduce a discrete-time Markov chain for exact performance analysis of multi-stage stochastic order fulfilment systems with customer-required stochastic order deadlines and *LOR*. This model exactly calculates multiple performance measures, e.g., system throughput, utilisation, service level, for generally distributed input parameters. For capacity planning with performance constraints, we extend the Markov chain by the blackbox optimisation algorithm *Mesh Adaptive Direct Search*. By this, we can determine the minimum capacity levels that are required to meet specific performance requirements of the customers. *LOR* is a beneficial control strategy for order fulfilment systems as it outperforms the dispatching policy *First come first serve*, especially in systems with high utilisation. For systems with utilisations of [0.9,1.0), we observe an average increase of α-service level of 18.3% and of β-service level of 2.5%. Furthermore, *LOR* achieves average capacity savings of 14%.

Key words: order fulfilment, workload balancing, discrete-time modelling, Markov chain, multi-stage system, deadline

1. Introduction

Order fulfilment “starts with receiving orders from the customers and ends with having the finished goods delivered” (Lin and Shaw 1998). In warehousing, order fulfilment typically consists of order picking, packing, and shipping, and flow shops in make-to-order production are multi-stage sequential order fulfilment processes. Order fulfilment systems are recently confronted with customer-required short order deadlines and a highly volatile customer demand consisting of low-volume orders (Van Gils et al. 2018, Kundu et al. 2020). To efficiently manage order fulfilment in this challenging environment, we propose workload balancing over time by using the variability buffers inventory, time, and capacity. The idea of variability buffers was introduced by Hopp and Spearman (2004) in the field of production systems, but it also applies for workload balancing in order fulfilment. Literature on order fulfilment incorporates several concepts for workload balancing among workstations (Portioli-Staudacher and Tantardini 2012, Kundu et al. 2020), workers (Bartholdi III and Eisenstein 1996), and picking zones (Jane and Laih 2005). For workload balancing over time, the concept of *flexible workforce planning* (Van Gils et al. 2017) uses the variability buffer capacity to flexibly adapt the provided capacity to the current workload, and the *Operational Workload Balancing Problem* (Vanheusden et al. 2020) combines the variability buffers time and capacity for workload balancing on an operational level. In contrast, we propose the *Strategy of*

Levelled Order Release (LOR) that exploits the variability buffers time and capacity for workload balancing over time on a tactical level.

2. *Strategy of Levelled Order Release (LOR)*

LOR comprises two planning problems: Capacity planning and order dispatching. It is inspired by the key ideas of Heijunka levelling in production systems. *LOR* reserves fixed capacities for order processing in each time period. During each time period, these capacities are then used to process orders according to ascending due dates (Mohring et al. 2020). By this, *LOR* initially exploits the time buffer of every order between its time of arrival and its deadline to balance the variability of the system workload. The remaining variability is then compensated by providing sufficient capacity. The required capacity levels derive from the specific performance requirements of the customers.

3. System Description

We describe an order fulfilment system by a *set of order types* $\mathcal{I}$, a *set of processes* $\mathcal{P}$, and a function $v : \mathcal{I} \rightarrow \{0,1\}^{p_{max} \times p_{max}}$ defining the *processing sequence* of the order types. Each order type $i \in \mathcal{I}$ is specified by the discrete stochastic parameters *number of incoming orders per time period* A_i and *lead time of an order* E_i. Each process $p \in \mathcal{P}$ is described by a discrete stochastic, order type-specific *processing performance per time unit* $L_{i,p}$ and a deterministic, order type-specific *capacity* $c_{i,p}$. As *LOR* reserves separate capacities for the order types $i \in \mathcal{I}$, we analyse them separately. The due dates of the orders are key for *LOR*. We consider orders with failed due dates, but we limit their backlog duration by a *maximum backlog duration* of R time periods.

4. Performance Analysis

For exact performance analysis of *LOR* in multi-stage stochastic order fulfilment systems with customer-required deadlines, we model these systems as a discrete-time Markov chain. We observe the order fulfilment system at discrete points in time $t \in \mathbb{N}_0$ that are integer multiples of a constant time period. The system state $\mathbf{X} = (X_{p,k})_{p \in \mathcal{P}, k \in \mathcal{K}}$ models the number of unprocessed orders in the order fulfilment system at the beginning of any time period. The state space is finite. The state transition consists of the sub-steps (1) order processing, (2) update of due dates, and (3) order income. Based on the limiting distribution of the Markov chain, we derive exact formulas of multiple performance measures for generally distributed input parameters: Number of unprocessed orders, number of lost sales per time period, utilisation, system throughput, time difference to order deadline of a completed order, α-, β-, and γ-service level. For all stochastic performance measures, we exactly calculate their entire probability distributions.

5. Capacity Planning

The capacity planning problem with performance constraints determines the minimum capacity levels c_p, $p \in \mathcal{P}$, that are required to meet specific performance requirements of the customers, e.g., a service level of at least 95%. It is a blackbox optimisation problem as the relationship between the provided capacity and the performance that is achieved with this capacity cannot be specified by an explicit mathematical equation. Instead, for each capacity, we calculate the corresponding Markov chain to quantify the performance that is achieved with this capacity. For solving the capacity planning problem, we use the blackbox optimisation algorithm *Mesh Adaptive Direct Search* (Audet and Dennis Jr 2006). This algorithm solves constrained blackbox optimisation problems with integer variables and outperforms other suitable algorithms regarding runtime efficiency.

6. Numerical Analysis and Application

It is difficult to find suitable benchmark strategies to evaluate *LOR* as it comprises two planning problems: Capacity planning and order dispatching. We use the dispatching policy *First come first serve (FCFS)* as a benchmark in the following and combine *FCFS* with the same fixed capacities per time period c_p, $p \in \mathcal{P}$, as *LOR* to ensure comparability.

For order fulfilment systems with utilisations smaller than 0.6, the differences between *LOR* and *FCFS* regarding α- and β-service level are neglectable small, i.e., maximum deviations of 0.63% for α-service level and 0.02% for β-service level. In contrast, when utilisation is high, *LOR* achieves higher service levels than *FCFS*. For systems with utilisations of [0.9,1.0), we observe an average increase of 18.3% for α-service level and 2.5% for β-service level. Furthermore, we achieve average capacity savings of 14% when using *LOR* instead of *FCFS*.

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Automated development of discrete-event simulation models for manufacturing systems with non-linear material flows

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Complex manufacturing systems require digital decision-support tools for reaching optimal production planning and control capabilities. Discrete event simulation models can be used to take prompt decisions at any time, provided the availability of an up-to-date model. Hence, techniques for a prompt model generation or adaptation to the physical system have to be developed. Literature is rich of approaches to generate digital models from available datasets. Yet, such techniques are mostly suited for managerial processes and cannot support properly manufacturing applications. This research regards the automated model generation for production systems. This paper addresses the discovery and representation of non-linear material flows, which are typical of several production systems such as assembly lines.

Key words: manufacturing systems; model generation; digital twins; Industry 4.0

1. Introduction

Simulation-based digital twins have recently emerged as effective tools to support both long- and short-term decision making in complex production environments [Macchi et al. (2018)]. The ability to take appropriate decisions exploiting digital models is strongly based on the assumption that models are properly aligned with the real system. However, manufacturing systems change regularly due to both external drivers and internal decisions (e.g., moving robots or machining stations). In this context, the time to develop a new model may hinder its exploitation along the production systems life cycle. Industry 4.0 contributed to the rise of new technologies for data acquisition, storing and communication, allowing for the knowledge of the shop floor status at anytime [Tao et al. (2018)]. The development phase of a model may be significantly shortened if it could be generated correctly from the available data in the manufacturing system. Recent approaches introduced the exploitation of process mining techniques [Van Der Aalst (2016), van der Aalst (2018)], which enable to retrieve the system topology from the manufacturing system data [Popovics and Monostori (2013)]. However, practical implementations of automated model generation remain scarce. Among the most significant issues, we highlight: (1) the difficulty in adapting the level of detail of the model, for removing complexities that may hinder both the understandability and the reusability of digital models [Nikula et al. (2020)]; (2) the discovery taking into account non-linear material flows; (3) the ability to automatically model complex behaviours of a real system, such as production policies and human behaviour; (4) the high sensitivity to rare events; (5) the inclusion of expert knowledge in the model building procedures. This work focuses on the model discovery taking into account non-linear flows of parts in the system.

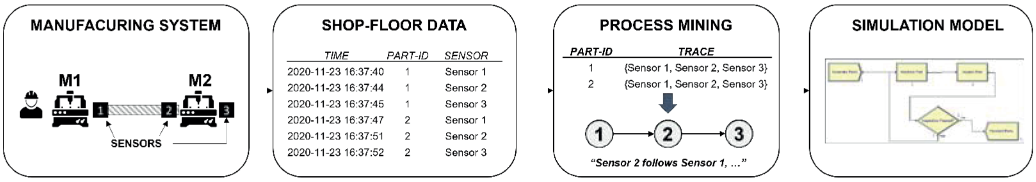

Figure 1. Graphical outline of automated model generation.

2. Model Generation for Non-linear Material Flows

Figure 1 shows an overview of the automated model development steps. The methodology starts with the extraction of valuable knowledge from production data logs. Then, precedences among activities can be retrieved from the combined information of sensors readings and part identifiers [Lugaresi and Matta (2021)]. The result is a graph model. In addition, manufacturing system properties and parameters such as buffer sizes are estimated from data through inference algorithms. Finally, the graph model is converted to an executable DES model.

The automated development of digital models for complex manufacturing systems reaches the limitations of the available methodologies. Indeed, most approaches based on process mining are limited by the assumption of so-called *flat data*. Namely, a unique part ID is used to identify material flows, while in realistic context several different object types may be involved in certain production phases (e.g., batches, packages, orders). The relationships among different objects are disregarded by the traditional methods. The result is that certain types of systems cannot be modelled entirely with an automated approach. For instance, in assembly processes several material flows converge toward assembly stations.

Let us consider as illustrative example the manufacturing system depicted in Figure 2. The system consists in five sectors: two manufacturing cells, two packaging cells, one end-of-line delivery sector. Each sector produces specific part types. Each item is traceable through a unique identifier (e.g., bar code, quick response code). Stations 1 and 2 produce components of type A, while stations 3 and 4 are dedicated to components B and C. Parts of type A and B are assembled into D-type products on station 5, while station 8 assembles components of type B and C in products of type E. Products D and E are joined to form a product type F in station 10. Each station is equipped with sensors and contributes to the creation of an event log. The model generation procedure from Lugaresi and Matta (2021) produces the graph model shown in Figure 2a. From the figure, it can be noticed that the result is a model with sectors treated as separate graph models. The same result is obtained with traditional process mining software tools (i.e., Disco, ProM). This is because model generation is strictly based on the single part identifier hypothesis. Since assembled parts have different identifiers from components, assembly relationships are neglected.

Figure 3 shows the method that has been developed to generate graph models taking into account non-linear object relationships. The method exploits data from the system (i.e., event log and bill of material) and the solution of a Job Assignment Problem to assign parts to their components at the corresponding assembly locations. The proposed method has been applied to test cases and a real manufacturing system structure, and has proved its applicability in all cases.

3. Impact and Future Developments

The proposed automated generation and tuning method can positively contribute to real-time simulation. Indeed, the online application of the proposed methodology allows for adapting simulation

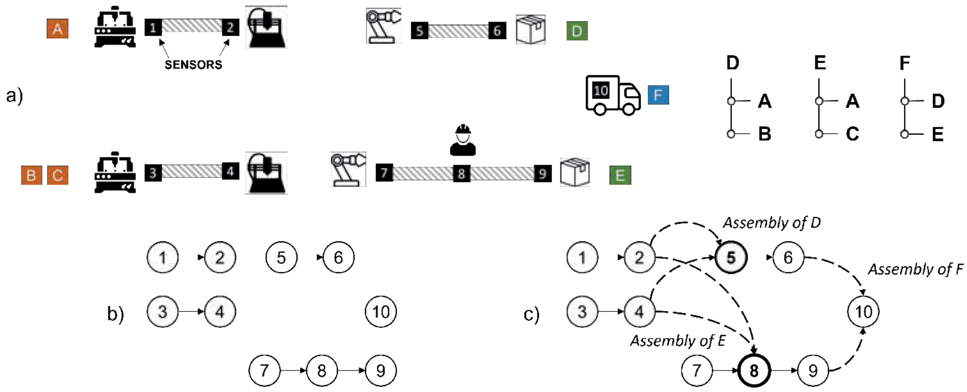

Figure 2. Graphical outline of (a) the generation of a graph model of a manufacturing system: (b) not considering assembly operations, (c) considering assembly relationships.

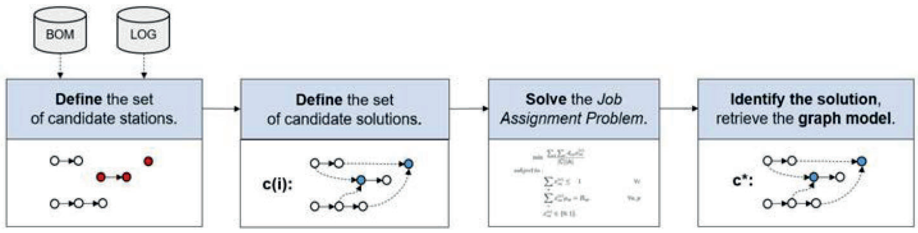

Figure 3. Graphical outline of the model generation method for non-linear material flows (i.e. assembly stations).

models to the real system counterpart, potentially at any time a modification occurs. Next developments of this research shall investigate the adjustments of the proposed approach to different types of manufacturing systems. For instance, job shops are characterized by several independent part flows, which may result in a more complex identification of the system structure. Future research should also focus on how to combine the results of different mining algorithms (e.g., material-based and information-based) in a unique and consistent framework.

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Session 9

Chair: Fikri KARAESMEN

Dynamic Routing with GNN for Overhead Hoist Transport Vehicles in Semiconductor Fab

Jaeho Lee
Ilhoe Hwang
Young Jae Jang*

Abstract

Automated material handling systems (AMHSs) play a critical role in semiconductor fabrication plants (fabs). The primary type of AMHS used in fabs is the overhead hoist transport (OHT) system, which transports lots between processing machines. A modern large-scale fab may operate thousands of OHT vehicles and thus often experiences OHT vehicle congestion. This paper proposes a reinforcement learning-based dynamic routing algorithm to address the OHT vehicle congestion problem, and develops a graph neural network–based predictive model to determine in advance the situation on an OHT vehicle's succeeding track. This predictive model enables the algorithm to function well, regardless of the distribution of data and the topology of the track. We show via simulation that this novel algorithm reduces the mean OHT vehicle travel time even under uncertain environment such as OHT vehicle failures. We also demonstrate how the proposed model can be applied to a commercial OHT management system.

1 Introduction

The process of forming modern semiconductor wafers consists of numerous steps performed by complex auxiliary machines. Bundles of 25 wafers are loaded into a unit called a front-opening unified pod (FOUP) for transport via an overhead hoist transport (OHT) system to the machine that performs each step. Thus, an OHT system forms the backbone of an automated material handling system (AMHS) in a fab, as shown in Figure 1.

The details of OHT systems, their performance measures, and operational aspects can be found in Hwang and Jang (2020) Due to recent increases in production, most semiconductor fabs now operate thousands of OHT vehicles on a track. Such large-scale systems may suffer from severe OHT vehicle congestion, especially as many OHT routes overlap and thus OHT vehicles often become concentrated in certain locations. This congestion increases OHT vehicle travel time, thereby increasing the overall cycle time of a product. In worst-case situations, a deadlock occurs, which means that the passage of OHT vehicles is halted. An intuitive way to solve this problem is for OHT vehicles to be able to recognize congestion before encountering it, and thus select a route to use that avoids congestion. In this study, Q routing is used as a route-selection method in the context of congestion. Q routing is a reinforcement learning algorithm that receives a reward based on the edge travel time described in Hwang and Jang (2020). However, a disadvantage of Q routing is its delayed adaptation in updating a Q value; that is, it updates a Q value after an OHT vehicle has completed traversing an edge, which means that the time it uses for route decision-making is different from the actual edge travel time. In this study, we solve this delayed adaptation problem by developing predictive model for edge travel-time, which determines the predicted edge travel time as a Q value before an OHT vehicle traverses an edge. This enables a process denoted active Q routing, whereby an OHT vehicle is routed to a non-congested edge. The predictive model is

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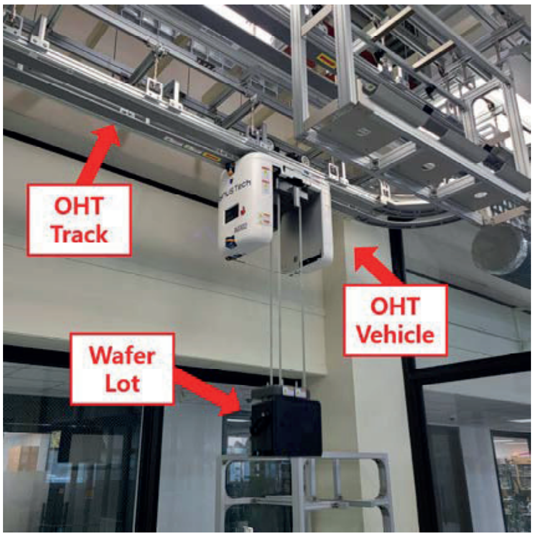

Figure 1: Components of an overhead transport system

based on a graphical neural network (GNN), which ensures that the adjacency status of the track and related information is effectively embedded in the OHT system. In comparison to other models that use the entire set of data from a map, our GNN-based model uses only surrounding edge data and thus has greatly improved learning speed. The excellent predictive accuracy of our GNN is demonstrated by its r_2 score of 0.9.

2 Problem and Approach

Figure 2 shows an example of a traveling OHT vehicle with a given Q value. When an OHT vehicle arrives at node 7, $Q[(d,6),7]$ is updated with the edge traveling time. This travel time is used to generate a current Q value, and this delayed adaptation is denoted a post update. In addition, when an OHT vehicle arrives at a branch node, such as node 7, it selects its next destination node based on the Boltzmann softmax action policy between Q values.

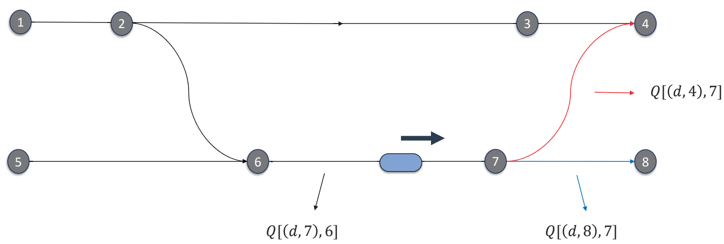

Figure 2: Example of the route selection

$$R[(d,i),j] = t(i,j) + \rho\{\varphi(d,j) - \varphi(d,i)\} \tag{1}$$

$$\delta_t = R[(d,i),j] + \gamma min_k Q[(d,j),k] - Q[(d,i),j] \tag{2}$$

However, a post update approach can cause problems, and thus we develop an active update approach to represent the edge travel time before an OHT vehicle traverses a given edge. The edge travel time $t(i,j)$ is replaced by the predicted edge travel time $\tilde{t}(i,j)$ in 1.

Figure 3 shows a typical problem caused by use of a post update approach. Suppose that the vehicle close to the Tool 3 has an unexpected temporal failure casing blockage of the following vehicles as depicted in the figure. Despite the obvious severe congestion on edge $(2, 3)$, the blue OHT vehicle cannot recognize it. This is because no OHT vehicle on edge $(2, 3)$ has completed traversing the edge, and the congestion on this edge is not yet reflected in its Q-value. Thus, the blue OHT vehicle may choose node 3 as its next node. In contrast, our active update approach detects this congestion before the blue OHT vehicle begins traversing edge $(2, 3)$, such that this vehicle recognizes the Q value of the edge and consequently detours to node 6.

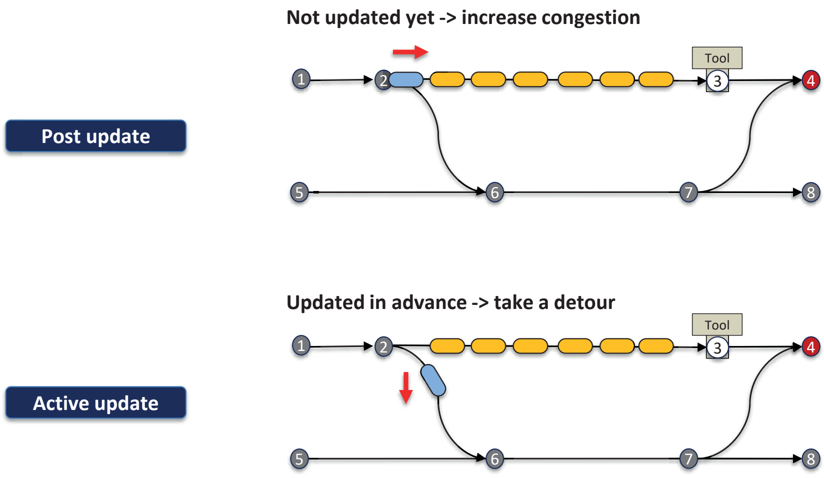

Figure 3: Problem arising from the use of a post update approach

2.1 Description of the GNN predictive model

Our novel predictive model for edge travel-time is based on a GNN, and the overall predictive procedure is illustrated in Figure 4. We define the machine learning task as the regression, which is a typical form of supervised learning. The predictive model is divided into two parts: a message-passing part based on high-level representation extraction, and a regression part.

The message-passing framework is a spatial-based convolutional GNN that learns a high-level representation of each node in a graph, meaning a representation of remote nodes that are the same distance from the target node. Thus, in Figure 5, the neighboring nodes of the blue target node A are denoted level 1 nodes, and the neighboring nodes of the level 1 nodes are denoted level 2 nodes. Therefore, by twice aggregating the information for the neighboring nodes of each node, the information from a given level can reach to the target node. This

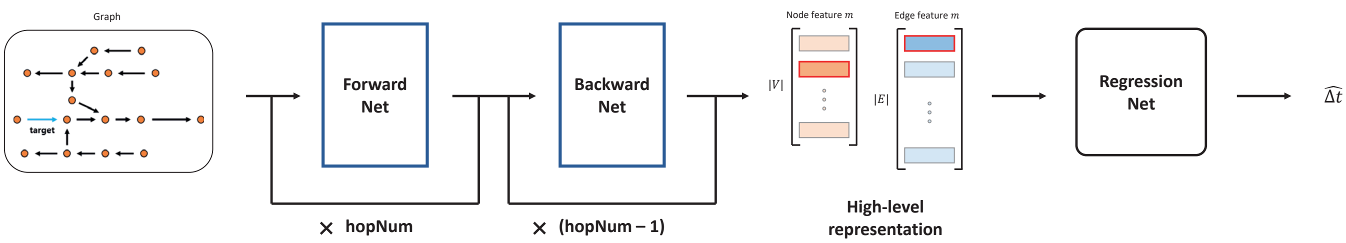

Figure 4: Summary of the predictive model

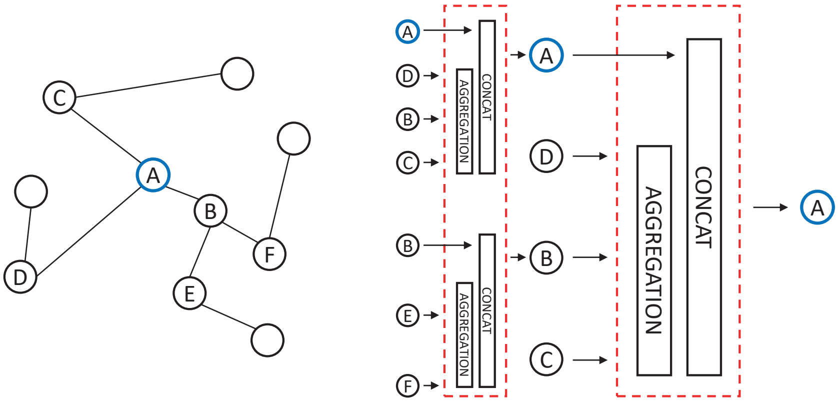

Figure 5: Description of message passing

aggregation can be performed using various forms of the adjacent matrix. Our predictive model is based in particular on GraphSAGE, a general inductive framework Hamilton et al. (2017). Once information that is as far as a given distance has been collected through the message passing framework, the final value is extracted by a fully connected regression network. The target value predicted by the model should not be the scale of the travel time; rather, it should be the additional travel time caused by congestion.

Our simulation tests show that the proposed model well predicts the congestion for small and moderate sized semiconductor fabs. We also demonstrate how the model can be applied to the actual operation of OHT in a real-fab environment.

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Cut-off Service-levels - some insights

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Keywords: keyword Cut-off time, keyword Service-level, keyword Service Operations

1. Problem Statement

Many services in Supply Chains, for instance warehousing services are contracted with a clause: *All orders received until 5 p.m. will be shipped until 7 p.m.*. Here, 5 p.m. is the cut-off time, and 7 p.m. is the deadline for processing in the warehouse. If the amount of orders and therefore the workload is stochastic, usually it is expected, that the above guarantee is not met every day. Instead, some deviation from the target is usually accepted, which is very similar to the service level which is used in inventory management.

Service-levels can be defined similar to α- and β-Servicelevels, Uta Mohring has also defined a γ-Service Level in her Ph.D.-Thesis. Intuitively, the definition of the service-levels can be derived from the respective Service-level definitions in Inventory Management. α-Service-level is the fraction of for instance days in a month, where the deadline has not been met for all orders arriving before the cut-off time. β-Servicelevel is then the fraction of orders or order-lines (depending on the service level agreement) which (for instance within a month) which have been shipped at the deadline, when submitted to the warehouse before the cut-off time.

Based on conversations during the 2019 SMMSO[1] we started to discuss, how to approach this task from a quantitative point of view for the operation. Several decisions have to be made in this context:

- How big should your work force be in order to match the service level goal?
- that question is closely linked to the question, how should the workforce distributed during the day, is it for instance better, to start as soon as possible or is procrastination not so bad after all - starting late has it's advantages?

Making these decisions requires the capability, to compute the expected service level, given an available capacity.

[1]Thanks again tho Stefan Helber and his team

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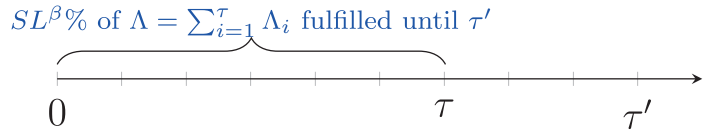
It is assumed, that the planning horizon is divided into $i \in \{1, \dots, , \tau, ..., \tau'\}$ periods with cut-off period τ and deadline τ'. Let Λ_i be the random variable of the number of arrivals in period i with $\Lambda = \sum_{i=1}^{\tau} \Lambda_i$ representing the cumulated arrivals up to cut-off time τ. Formulating the cut-off condition as an β-service level, we need to ensure that expected fraction of fulfilled demand Λ is at least SL^β.



$$\mathbf{E}\left[\frac{\sum_{i=1}^{\tau'} Th_i}{\Lambda}\right] \geq SL^\beta \tag{1}$$

Let Th_i be the random variable of the throughput (number of served arrivals) for period i. Th_i depends on all parameters and decisions up to period i.

2. Performance evaluation

For the analytical performance evaluation we use a workload formulation.

The number of arrivals in period i is distributed according to a homogeneous renewal process with time-dependent rates λ_i for $i \leq i_{\tau'}$. The probability distribution p_j^a describes the distribution of the number of arrivals Λ_i in a period i: $\mathrm{p}_j^a = P(\Lambda_i = j) \forall j \in 0, \dots j_{max},\ i \in 1, \dots i_{\tau'}$

Processing times are generally distributed with rate μ for each of the identical parallel servers c_i. The number of parallel servers results from the decision on the number x_s of selected shifts $s \in \{1, \dots, S\}$ with the indicator parameter $a_{is} = \{ 1\ if period i is covered by shift s$ $0 else$.

W is a discrete random variable, which describes the workload, which is associated with one arrival (and $E(W) = 1/\mu$). The workload distribution is described by $p_l^b = P(W = l)$ as the probability, that it takes l time units to serve an arrival on one server.

The probability distribution of the total workload W_i^{tot} arriving in a period i can then be computed by weighing the respective j-fold convolution of the workload with the probability $p_{i,j}^a$ of seeing j arrivals in period i.

$$W_i^{tot} = \sum_{j=0}^{j_{max}} p_{i,j}^a \cdot *^j p^b \tag{2}$$

The n-th element of the vector $W_{i,n}^{tot}$ describes the probability, that the new workload which has arrived in a period is exactly n time units.

2.1. Separated arrival and service phases

In the following we consider a model where the arrival phase is separated from the service phase. Arrivals may happen until the cutoff time τ, i.e., $\lambda_i = 0$ for $i > i_\tau$. The number of servers equals zero until the cutoff time τ, i.e., $c_i = 0$ for $i \leq i_\tau$.

In this special case, the workload is the sum of all arriving workload in the periods until τ. Thus the random variable $\overline{W}_\tau^{tot}$ is the sum of a fixed number of random variables and is computed by the convolution of the workload arriving in all previous periods: $\overline{W}_\tau^{tot} = *_{i=0}^{\tau} W_i^{tot}$

The cumulative distribution $\overline{F}_\tau^W$ of the total workload having arrived until τ can now be used to compute the service levels SL^α and SL^β with respect to a chosen capacity. The Elements of $\overline{F}_\tau^W$ are computed as: $\overline{F}_{\tau,j}^W = \sum_{n=0}^{j} \overline{W}_{\tau,n}^{tot}$

The SL^α which can be achieved with a capacity c is computed by comparing the achievable workload $k = \sum_{i=i_\tau+1}^{i_{\tau'}} c_i$ with the cumulative distribution $\overline{F}_\tau^W$ of the total workload having arrived until τ. The smallest index n where $\overline{F}_{W,n} n \leq k$ is the SL^α.

The SL^β is determined by the probability weighed fraction of unfinished work compared to the total workload. The amount of unfinished work achieved with a capacity decision is again k. The expected unfinished work B is determined with

$$B = \sum_{n>k} \overline{W}_{\tau,n}^{tot} \cdot (n-k) \tag{3}$$

The service level β with respect to the workload criterion is

$$SL^\beta = 1 - \frac{B}{E(\overline{W}_\tau^{tot})} \tag{4}$$

The utilization of the capacity can easily be computed by $\rho = \frac{\Lambda}{k\mu} = \frac{E(W_\tau^{tot})}{k}$ and provides vital information about the efficiency of the system.

From $\overline{F}_\tau^W$ we can directly derive the α-Servicelevel. The computation of the β-Servicelevel requires the computation of the unfinished work and the associated likelihood and combining it into the expected backlog B.

$$B = \sum_{n>k} \overline{W}_{\tau,n}^{tot} \cdot (n-k) \tag{5}$$

Thus $SL^\beta = 1 - \frac{B}{E(\overline{W}^{tot})}$.

Another important performance indicator in practice is the utilization of the capacity.

2.2. Combined Arrival and Service Phases

we will also demonstrate, how to handle Phases, where new orders are arriving while others are already processed.