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Modelo de programação da produção preditiva-reativa orientada a dados de estoque integrando *machine learning* e otimização baseada em simulação

Florianópolis
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Orientador: Prof. Enzo Morosini Frazzon, Dr.-Ing.

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O presente trabalho em nível de doutorado foi avaliado e aprovado por banca examinadora composta pelos seguintes membros:

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Florianópolis, 2022.

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“Comece fazendo o que é necessário, depois o que é possível, e de repente você estará fazendo o impossível.” (São Francisco de Assis)

“Cominciate col fare ciò che è necessario, poi ciò che è possibile. E all’improvviso vi sorprenderete a fare l’impossibile.” (San Francesco d’Assisi)

RESUMO

A programação da produção é um importante processo de tomada de decisão nas indústrias, tendo a finalidade de alocar de maneira ideal os recursos limitados para tarefas de processamento ao longo do tempo. Além disso, as indústrias lidam com uma ampla gama de perturbações que colocam em risco a sua produtividade. Para auxiliar neste desafio, os sistemas de programação da produção no contexto da Indústria 4.0, devem incorporar mecanismos com recursos inteligentes para buscar um desempenho ideal e a reatividade da operação, independentemente de qualquer cenário. Assim, a adoção de estratégias como a programação preditiva-reativa é estudada para garantir que o processo seja realizado mantendo um bom desempenho operacional. Os problemas mais comuns na literatura que abordam a programação preditiva-reativa lidam com perturbações como a quebra da máquina, modificação do pedido e/ou cancelamento. No entanto, problemas com disponibilidade de estoque também causam interrupções na programação e ainda há oportunidades de pesquisas. Nesse contexto, a presente tese tem como objetivo propor um modelo para a programação da produção preditiva-reativa orientada a dados de estoque provenientes do chão de fábrica. O estudo foi elaborado na forma de coletânea de artigos e estruturado em três fases: (*i*) Definição do problema de pesquisa e desenvolvimento do modelo conceitual, (*ii*) Construção do modelo computacional e caso teste e (*iii*) Análise do desempenho operacional do modelo proposto em um estudo de caso. O modelo proposto combina uma técnica de aprendizado de máquina, a rede neural artificial com o algoritmo genético, para fornecer periodicamente a programação preditiva, considerando um melhor cenário de acordo com um indicador chave de desempenho. Porém, com a dinâmica do mundo real, a indisponibilidade de material causa rupturas na produção, o que aciona o método de otimização baseada em simulação para lidar com esses eventos. Então, este método fornece uma programação reativa que é um conjunto otimizado de regras de prioridade para sequenciar os trabalhos em cada máquina de acordo com os dados atuais do chão de fábrica. O modelo foi validado através de simulação computacional de um estudo de caso utilizando dados reais de uma empresa. Os resultados mostraram que, o modelo proposto foi capaz de aumentar de 75,2% para 80,7% o nível de serviço, impactando em uma redução no valor médio das entregas atrasadas ao cliente em 22%. Assim, mesmo em um cenário dinâmico e estocástico, com quebras de máquinas, problemas de qualidade, atrasos de matéria-prima e problemas de acuracidade de estoque, o modelo mostrou-se eficiente para mitigar os efeitos dessas variações. Em termos teóricos, esta tese visa contribuir para a ampliação do horizonte de pesquisas sobre o tema abordado, apresentando um modelo único, ainda não explorada no meio científico. Em termos práticos, o modelo busca fornecer uma melhor compreensão dos problemas inerentes à indisponibilidade de material, reduzindo a incerteza das informações e fornecendo conhecimento sobre os dados do chão de fábrica. Além disso, permite que a tomada de decisão seja mais rápida e inteligente, apresentando soluções que melhoram a eficiência operacional da programação da produção, promovendo a competitividade das empresas.

Palavras-chave: Programação da produção. Programação preditiva-reativa. Estoque. Indústria 4.0. Aprendizado de máquina. Otimização baseada em simulação.

ABSTRACT

Production scheduling is an important decision-making process in industries, aiming to optimally allocate limited resources to processing tasks over time. In addition, industries deal with a wide range of disturbances that place their productivity at risk. This challenge requires that production scheduling systems, in the context of Industry 4.0, incorporate mechanisms with intelligent features to seek optimal performance and reactivity of the operation, regardless of any scenario. Thus, the adoption of strategies such as predictive-reactive scheduling are studied to ensure that the process is executed while maintaining good operational performance. The most common problems in the literature that address predictive-reactive scheduling deal with disruptions such as machine breakdown, order modification, and/or cancellation. However, problems such as material non-availability also cause scheduling disruptions and there are still opportunities for research. In this context, this thesis aims to propose an approach for predictive-reactive production scheduling based on inventory data from the shop floor. The study was organized as a collection of papers and structured in three phases: (*i*) Definition of the research problem and development of the conceptual model, (*ii*) Construction of the computational model and test case, and (*iii*) Analysis of the operational performance of the proposed approach in a case study. The proposed approach combines a machine learning technique, artificial neural network with genetic algorithm, to periodically provide predictive scheduling by considering a best-case scenario according to a key performance indicator. However, with real-world dynamics, material non-availability causes disruptions in production, which triggers the simulation-based optimization method to handle these events. Then, this method provides a reactive scheduling that is an optimized set of priority rules to sequence the jobs on each machine according to the current shop floor data. The approach was validated through computer simulation of a case study using real data from a company. The results showed that the proposed approach was able to increase the service level from 75.2% to 80.7%, impacting on a reduction in the average value of delayed deliveries to the customer by 22%. Thus, even in a dynamic and stochastic scenario, with machine breakdowns, quality problems, raw material delays, and inventory accuracy problems, the approach proved efficient to mitigate the effects of these variations. In theoretical terms, this thesis seeks to contribute to the expansion of the research horizon on the subject, presenting a unique approach, not yet explored in the scientific environment. In practical terms, the approach seeks to provide a better understanding of the problems inherent to material non-availability, reducing the information uncertainty and providing knowledge about the shop floor data. Furthermore, it allows faster and smarter decision making, presenting solutions that improve the operational efficiency of production scheduling, promoting the competitiveness of companies.

Keywords: Production scheduling. Predictive-reactive scheduling. Inventory. Industry 4.0. Machine learning. Simulation-based optimization.

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LISTA DE ABREVIATURAS E SIGLAS

ABNT	Associação Brasileira de Normas Técnicas
ANN	*Artificial Neural Networks*
BP	*Bibliographic Portfolio*
CAPES	Coordenação de Aperfeiçoamento de Pessoal de Nível Superior
CM	*Conceptual Model*
CPS	*Cyber Physical Systems*
DES	*Discrete Event Simulation*
DOI	*Digital Object Identifier*
DT	*Digital Twin*
EDD	*Earliest Due Date*
ERP	*Enterprise Resource Planning*
FIFO	*First In First Out*
GA	*Genetic Algorithm*
IoT	*Internet of Things*
IT	*Information Technology*
JIT	*Just-In-Time*
KPI	*Key Performance Indicator*
MDA	*Machine Data Acquisition*
MDD	*Modified Due Date*
MES	*Manufacturing Execution System*
MILP	*Mixed-Integer Linear Programming*
ML	*Machine Learning*
MP	Matéria-Prima
MRP	*Material Requirement Planning*
NA	*Not Applicable*
NI	*Not Informed*
ODD	*Operational Due Date*
P	*Predictive scheduling*
PB	Portfólio Bibliográfico
PCP	Planejamento e Controle da Produção

PDA	*Production Data Acquisition*
PPC	*Production Planning and Control*
PPGEP	Programa de Pós-Graduação em Engenharia de Produção
PR	*Predictive-Reactive scheduling*
ProKnow-C	*Knowledge Development Process – Constructivist*
PS	*Production Scheduling*
R	*Reactive scheduling*
RSL	Revisão Sistemática da Literatura
SBO	*Simulation-Based Optimization*
SL	*Service Level*
SLR	*Systematic Literature Review*
SLK	*Least Global Slack*
SPT	*Shortest Processing Time*
UFSC	Universidade Federal de Santa Catarina
WIP	*Work-In-Process*

SUMÁRIO

CAPÍTULO 1

1 INTRODUÇÃO

1.1 CONTEXTUALIZAÇÃO

A programação do uso dos recursos produtivos é uma importante função do planejamento e controle da produção (PCP). Em um sistema produtivo, cada tarefa requer certas quantidades de recursos especificados para um intervalo de tempo determinado, chamado de tempo de processamento. Os recursos incluem o uso de equipamentos, a utilização de matéria-prima ou intermediários, o emprego de operadores, entre outros. Além disso, as tarefas envolvem a transformação química ou física de materiais, transporte de produtos ou intermediários, operações de limpeza e manutenção, entre outros. O objetivo da programação da produção é alocar recursos limitados às tarefas de processamento ao longo do tempo (LI; IERAPETRITOU, 2008). Ou seja, a programação da produção possui a importante função de tomada de decisão, pois deve determinar quando a tarefa precisa ser processada, em que máquina processá-la ou qual a prioridade atribuída a tarefa (VALLEDOR *et al.*, 2018). Com isso, é possível utilizar efetivamente os recursos disponíveis para atingir metas relevantes de indicadores-chave de desempenho (*Key Performance Indicator*, KPI) para a organização.

No entanto, a programação da produção tem uma série de desafios. Por exemplo, os ambientes de produção são dinâmicos e incertos, com chegadas e/ou cancelamentos de tarefas, quebras de máquinas, falta de matéria-prima, problemas de qualidade, entre outros. As empresas de manufatura precisam lidar com toda esta complexidade a fim de melhorar a sua eficiência de produção e satisfazer os requisitos dos clientes. Para manterem-se competitivas, há uma urgência em aplicar tecnologias emergentes, como por exemplo, análise inteligente, ferramentas avançadas de previsão e sistemas *cyber*-físicos (*cyber-physical systems*, CPS), aos sistemas tradicionais de manufatura (LEE; KAO; YANG, 2014; OZTEMEL; GURSEV, 2020).

Nesse sentido, apresentado inicialmente na Alemanha em 2011, a quarta revolução industrial, mais conhecida como "Indústria 4.0", tem atraído muita atenção em literaturas recentes introduzindo a ideia de uma indústria totalmente integrada e eficiente (HOFMANN; RÜSCH, 2017). Hermann, Bücker e Otto (2019) comentam que a Indústria 4.0 promove um ambiente que integra máquinas e dispositivos físicos complexos com uma rede de sensores e *softwares*, de modo a prever, planejar e controlar melhores resultados para a empresa. Hermann, Pentek e Otto (2016) descrevem quatro princípios para o projeto da Indústria 4.0, sendo estes: a interconexão, a transparência de informações, a tomada de decisão descentralizada e a assistência técnica. Para os autores, a interconexão permite a conexão de máquinas, dispositivos, sensores e pessoas, os quais comunicam-se uns com os outros através da Internet das Coisas (*Internet of Things*, IoT). A transparência da informação permite que os sistemas de informação criem um gêmeo digital (*Digital Twin*) do mundo físico, enriquecendo os modelos de simulação virtual com dados de sensores em tempo real. Já a tomada de decisão descentralizada, permite mais autonomia na execução das tarefas, reduzindo a complexidade e o esforço de planejamento. Por fim, a assistência técnica permite que os seres humanos tomem decisões e resolvam problemas urgentes em curto prazo, utilizando dados e informações relevantes, provenientes da digitalização da manufatura.

A Indústria 4.0 promove diversas oportunidades e benefícios para toda a organização e, no âmbito dos sistemas de manufatura, impacta positivamente no monitoramento dos processos físicos e nas tomadas de decisões inteligentes. Estes benefícios ocorrem por meio da comunicação e cooperação em tempo real com humanos, máquinas, sensores, produção flexível e adaptativa e redução de custos de complexidade (HOFMANN; RÜSCH, 2017; ZHONG *et al.*, 2017). Elmaraghy *et al.* (2021) comentam que a transformação para uma manufatura inteligente (*Smart Manufacturing*) ocorre por meio da adoção de tecnologias que possibilitem que os dispositivos ou máquinas variem seus comportamentos em resposta a diferentes situações e exigências, baseadas em experiências passadas e capacidades de aprendizagem. Tecnologias como o CPS, IoT, computação em nuvem, computação orientada a serviços, inteligência artificial e ciência de dados, permitem a comunicação direta com os sistemas de manufatura. Uma vez implementadas, estas tecnologias viabilizam a resolução dos problemas e decisões adaptativas podem ser tomadas em tempo hábil (ZHONG *et al.*, 2017).

Frente a este novo contexto para os sistemas de manufatura, torna-se necessário que o PCP também disponha de novas abordagens, métodos e ferramentas para analisar os sistemas de produção, tendo em vista as metas e a organização ideal dos processos operacionais. Incrementar tecnologias advindas da Indústria 4.0 podem auxiliar na busca para a redução de custos, o equilíbrio do estoque e as capacidades disponíveis eficientemente aproveitadas (SEITZ; NYHUIS, 2015). Dessa forma, com o aumento crescente do uso de tecnologias nos processos, ocorre uma mudança de foco que coloca o PCP não mais como uma simples área de apoio, mas como um membro do grupo de fatores que determinam a competitividade da empresa (BUENO; GODINHO FILHO; FRANK, 2020).

Nesse sentido, a programação da produção tem sido amplamente explorada na literatura, principalmente por ser uma função essencial do PCP a qual auxilia na coordenação das tarefas de produção considerando os recursos disponíveis (NGUYEN; MEI; ZHANG, 2017). Duas estratégias para a programação da produção podem ser utilizadas em ambientes de incerteza e variabilidade: (i) a programação dinâmica e (ii) a programação preditiva-reativa (VIEIRA; HERRMANN; LIN, 2003). A programação dinâmica não permite atualizar as programações de produção. Nesta estratégia, métodos descentralizados de controle de produção são utilizados para despachar trabalhos quando necessário. Já a programação preditiva-reativa ocorre em duas etapas principais. Na primeira, gera-se uma programação inicial e na segunda, ocorre a atualização dessa programação em resposta aos eventos que a interromperam (CHAARI *et al.*, 2014). Devido ao seu princípio simples, de fácil implementação e flexibilidade de atualização da programação, a estratégia preditiva-reativa é a mais praticada nos sistemas de manufatura (OUELHADJ; PETROVIC, 2009; ZHUANG *et al.*, 2022).

Vieira, Herrmann e Lin (2003) comentam que alguns dos principais eventos identificados na literatura para realizar a programação preditiva-reativa, são: falha de máquina, chegada urgente de ordens, cancelamento de ordens, mudança na data de entrega da ordem (atraso ou adiantamento), mudança na prioridade da ordem. No entanto, a disponibilidade de material – estoque de materiais – é um outro evento que varia com relação ao tempo e está frequentemente sujeito a desvios inesperados, causando a necessidade de alterações na programação da produção já estabelecida (CALAHORRANO *et al.*, 2016). Adicionalmente, o estoque desempenha um papel importante na programação tendo um grande impacto nos custos gerais de fabricação (LUH; ZHOU; TOMASTIK, 2000). Entretanto, observa-se uma lacuna de pesquisa com relação a integração de dados de estoque com a programação da produção, ou seja, uma programação que reaja frente aos eventos de indisponibilidade de material. Mas com a crescente quantidade de informações disponíveis no chão de fábrica, provenientes das tecnologias aplicadas da Indústria 4.0, diferentes métodos podem ser desenvolvidos para abordar requisitos e necessidades industriais específicas (ELMARAGHY *et al.*, 2021). Dessa forma, a rapidez na coleta de informações no chão de fábrica, possibilita acompanhar em tempo real os níveis de materiais e intervir com tratativas para mitigar o atraso na produção por falta de estoque (BALUGANI *et al.*, 2018).

Diante do contexto exposto, esta tese propõe um modelo para a programação da produção preditiva-reativa orientada a dados de estoque provenientes do chão de fábrica. Corroborando com a perspectiva da Indústria 4.0, os dados da disponibilidade de material serão utilizados em tempo real para controlar a programação. Uma programação preditiva será inicialmente gerada com o intuito de fornecer uma programação com menor possibilidade de rupturas durante a execução da produção. Porém, caso haja a falta de material, este evento aciona a programação reativa que adapta a programação inicial ao novo cenário. Desta forma, este modelo propicia uma programação preditiva-reativa mais assertiva, mitigando o não cumprimento das entregas aos clientes e que ocorre de forma automática, sem a intervenção do planejador. No entanto, os planejadores e gerentes tem acesso as informações relevantes para o monitoramento e tomada de decisões necessárias.

1.2 DEFINIÇÃO DO PROBLEMA

Considerando a introdução dos conceitos da Indústria 4.0, tem-se despertado uma grande ênfase para que os sistemas de manufatura se tornem cada vez mais integrados e inteligentes, estimulando avanços nas técnicas tradicionalmente adotadas (CHEN, 2017). Vários processos têm sido atualizados para seguir as tendências apontadas pela quarta revolução industrial, assim como o processo da programação da produção (UHLMANN; FRAZZON, 2018).

Uma das oportunidades para esta transformação, seguindo a perspectiva da Indústria 4.0, é a abordagem de sistemas adaptativos, que conseguem lidar com uma ampla gama de perturbações/eventos inesperados do chão de fábrica, os quais colocam em risco a execução da programação de produção (ELMARAGHY *et al.*, 2021). Estes eventos podem ser os pedidos urgentes que chegam, pedidos que são cancelados, quebras e manutenções das máquinas, atrasos no tempo de processamento, retrabalho ou problemas de qualidade, material indisponível ou mudança de recursos (HUANG; LIAO, 2012; SCHUH *et al.*, 2017).

Nesse ambiente de incertezas, um dos grandes desafios do PCP é sem dúvida o controle dos estoques. Os materiais podem ser armazenados como estoques de matéria-prima, material em processo (*work-in-process*, WIP) e produtos acabados (WIDYADANA; WIDJAJA; LIONG, 2017). Andwiyan, Irsan e Murad (2017) comentam que os estoques são necessários para evitar a escassez ou excedentes para que os processos da produção não sejam obstruídos. Assim, uma das principais metas do PCP é regular a quantidade de itens em estoque.

Corroborando a isto, frente a situação atual, caracterizada por crises epidêmicas, mudanças de produtos e desvios no tempo de reposição, pode-se haver rupturas de estoque e um alto nível de estoque necessário para fornecer um determinado nível de serviço (GALLEGO-GARCÍA; GALLEGO-GARCÍA; GARCÍA-GARCÍA, 2021). Com a crise global da COVID-19, diversas empresas estão ainda sofrendo com a falta de abastecimento e consequentemente, os consumidores também são afetados, uma vez que as empresas especulam sobre a oferta da demanda e reduzem a oferta para aumentar as margens devido à demanda dos clientes (CHOWDHURY *et al.*, 2020).

Dessa forma, torna-se evidente que a falta de material é um dos eventos que tem grande impacto na execução da programação da produção. Tal perturbação pode ser classificada de baixo impacto, isto é, pode ser recuperada em um tempo razoável, ou de alto impacto, quando não pode ser recuperada em um momento viável com relação à duração da programação gerada (PETROVIC; DUENAS, 2006). Entretanto, aumentar o nível de estoque de matéria-prima, pode levar a um excesso, criando a necessidade de espaço físico, equipamentos e mão-de-obra para transportar, estocar e gerenciar o estoque sem valor agregado. Além disso, os defeitos são mais difíceis de detectar, gerando retrabalhos e refugos (WIDYADANA; WIDJAJA; LIONG, 2017). Adicionalmente, manter estoques de WIP para absorver as incertezas no ambiente dinâmico do chão de fábrica, representa um investimento financeiro considerável e grandes esforços para serem controlados. Os estoques de WIP escondem na maioria das vezes problemas relacionados à produção, como a permanência excessiva do produto nas operações intermediárias do processo, causando atrasos desnecessários e má qualidade dos produtos (KANG *et al.*, 2017). Ainda, Bose (2006) comenta que o excesso de estoque de produtos acabados também deve ser evitado, pois indica o uso de recursos em antecipação à necessidade do cliente, não promovendo um processo enxuto e acarretando em custos desnecessários.

Há um enorme espaço de soluções para buscar resolver os desafios da programação da produção, por isso tais problemas são conhecidos como *NP-hard* (*non-deterministic polynomial-time hardness*). Isso significa que, o esforço computacional para obter uma solução otimizada cresce exponencialmente com o número de operações e o número de máquinas consideradas (BAKER; TRIETSCH, 2013). Uma das tratativas de solução é a reprogramação a partir do zero para gerar uma nova programação quando a ruptura ocorre (BARTÁK; VLK, 2015). Porém, a coleta de informações e a reprogramação total envolvem um tempo excessivo que pode levar à falha do mecanismo de programação e, portanto, ter consequências de longo alcance. Assim, encontrar a melhor resposta para a programação da produção é bastante desafiador, por isso a maioria dos estudos buscam uma solução rápida, mas eficaz para a implementação prática (MURAD *et al.*, 2022).

Frente ao contexto exposto e os desafios enfrentados pela programação da produção, este estudo tem como objetivo final responder a seguinte questão de pesquisa: "*Como executar a programação da produção preditiva-reativa baseada em dados de forma a mitigar a não disponibilidade de material e aprimorar o desempenho operacional do sistema produtivo?*".

1.3 OBJETIVOS

Considerando a contextualização e o problema de pesquisa apresentados, os objetivos geral e específicos desse estudo são apresentados a seguir.

1.3.1 Objetivo geral

Propor um modelo de programação da produção preditiva-reativa orientada a dados de estoque provenientes do chão de fábrica.

1.3.2 Objetivos específicos

1) Identificar na literatura as principais abordagens referentes a programação da produção preditiva-reativa, bem como os principais métodos já adotados inerentes à sua implementação;
2) Propor um modelo conceitual para a programação da produção preditiva-reativa orientada a dados de estoque;
3) Identificar na literatura as principais técnicas de *machine learning* para viabilizar a programação preditiva;
4) Validar o método da otimização baseada em simulação para gerar a programação reativa;
5) Mensurar o desempenho operacional do modelo desenvolvido por meio de simulação computacional, considerando um cenário real de uma empresa de manufatura.

1.4 JUSTIFICATIVA E RELEVÂNCIA

Comumente, a decisão do planejamento da produção, especialmente a programação, é resolvida por meio da intuição, experiência e julgamento (CHAN; AU; CHAN, 2006). No entanto, devido a rupturas que ocorrem na programação, provenientes de incertezas, torna-se necessário o desenvolvimento de abordagens para solucionar os impactos dessas incertezas, de modo a buscar uma maior estabilidade na execução da produção (SOBASZEK; GOLA; ŚWIĆ, 2017).

Tais incertezas geram uma preocupação muito grande nos sistemas de manufaturas reais, uma vez que muitos parâmetros que estão associados a programação da produção podem não ser exatamente conhecidos. Parâmetros que podem variar com relação ao tempo, como a disponibilidade de matéria-prima, preços, confiabilidade da máquina e exigências do mercado, estão frequentemente sujeitos a desvios inesperados (CALAHORRANO *et al.*, 2016).

Nesse sentido, encontra-se na literatura diferentes tratativas para a implementação da estratégia de programação da produção preditiva-reativa, todas com o intuito de ajudar o sistema de manufatura a funcionar de forma mais produtiva e eficiente. Alguns artigos descreveram algoritmos para gerar ou atualizar programações de produção (BOŻEK; WYSOCKI, 2016; COWLING; OUELHADJ; PETROVIC, 2004; SUN; XUE, 2001). Outros estudos apresentaram novas políticas de reprogramação que especificam quando as programações de produção são geradas e atualizadas (KALINOWSKI; KRENCZYK; GRABOWIK, 2013; KLIMEK; LEBKOWSKI, 2011; PETROVIC; DUENAS, 2006). Ainda, algumas pesquisas apresentaram estudos sobre regras de prioridade, políticas de controle ótimo ou outras abordagens para a reprogramação (GUIZZI; VESPOLI; SANTINI, 2017; JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018; SAKAGUCHI *et al.*, 2008; VALLEDOR *et al.*, 2018).

A literatura também relata importantes resultados provenientes da implementação desta estratégia. No artigo de Lee, Kang e Park (1996), os autores desenvolveram um sistema de programação colaborativo (*Collaborative Scheduling System*), com o objetivo de reconfigurar a programação existente com os dados de monitoramento coletados do chão de fábrica. Os resultados obtidos desta aplicação foram a redução de 25% em média no *lead time* de produção e a melhoria na utilização da máquina de 10 para 20%. Garcia *et al.* (2008) desenvolveram uma ferramenta multiagente para proporcionar uma programação flexível, tolerante a falhas e programável. Os autores aplicaram o protótipo em uma indústria de cerâmica e concluíram que, a ferramenta é confiável, robusta, flexível e eficiente sob condições normais, bem como em circunstâncias de perturbações na programação. Já os autores Pach *et al.* (2014), desenvolveram uma arquitetura híbrida para alternar de forma dinâmica entre as programações preditiva e reativa, caso ocorresse um evento que proibisse o comportamento planejado a ser seguido. Os resultados da aplicação dessa arquitetura mostraram que, a produção pode ser concluída de acordo com o comportamento planejado, proporcionando ganhos significativos no desempenho geral do sistema de manufatura.

Contudo, apesar dos diferentes estudos desenvolvidos abordando tal estratégia, a perturbação (evento) que tem sido mais frequentemente explorada na literatura como um gatilho para a reprogramação, é a quebra de máquina (LI; IERAPETRITOU, 2008; PAPROCKA, 2019; PAPROCKA; SKOŁUD, 2013; PETROVIC; DUENAS, 2006). Porém, os dados de estoques também influenciam diretamente os sistemas de manufatura, impactando na execução da produção (ZHOU *et al.*, 2017). Bose (2006) afirma que a indisponibilidade de material pode levar a rupturas de estoque, causando interrupções na produção e resultando em falhas no nível de serviço ao cliente. Além disso, a disponibilidade de estoque é geralmente considerada no planejamento a longo prazo. Tradicionalmente, há pouca possibilidade de responder à escassez, já que as quantidades mostradas estão planejadas para estar disponíveis e não atualmente disponíveis (WILD, 2017). Dessa forma, no nível operacional, quando a programação de produção está sendo executada, as perturbações podem alterar o *status* do sistema e afetar negativamente seu desempenho.

Adicionalmente, com advento da Indústria 4.0, novas abordagens de tecnologias promovem oportunidades de aplicações de forma integrada tantos nos processos produtivos quanto nos processos administrativos (RØDSETH *et al.*, 2017). Entretanto no Brasil, essa questão ainda é mais latente, já que o país ocupa 71ª posição no quesito competitividade, segundo o Relatório Global de Competitividade, publicado pelo Fórum Econômico Mundial em 2019 (SCHWAB, 2019). Há uma série de desafios no país para serem vencidos, além da pouca disseminação do tema. Porém, a quarta revolução industrial traz uma grande oportunidade para as empresas do Brasil se tornarem mais competitivas mundialmente.

Dessa forma, perante ao contexto exposto, identificou-se como oportunidade de pesquisa a proposição de um modelo que integre os dados de estoque à programação da produção, visando proporcionar um melhor desempenho operacional aos sistemas de manufatura. Pela atualidade do tema, considerando a perspectiva da Indústria 4.0; originalidade do estudo, buscando preencher uma lacuna de pesquisa; e a contribuição para o debate da comunidade científica, justifica-se o desenvolvimento desta tese.

Quanto a relevância, este estudo possui contribuição teórica e metodológica para o desenvolvimento científico. Em termos teóricos, esta tese contribui para preencher a lacuna atual de conhecimento sobre o impacto de dados de estoque na programação da produção, a curto-prazo, considerando o desempenho do chão de fábrica. Além disso, este estudo contribui para a literatura, pois apresenta um modelo conceitual dentro do contexto da Indústria 4.0, para mitigar os impactos da falta de material durante a execução da produção. Em termos de relevância metodológica, esta tese propõe um novo modelo para superar as limitações dos métodos existentes, com predominância em modelos estáticos e determinísticos, numa perspectiva baseada em dados atuais que adapte o sistema de uma forma dinâmica.

Destaca-se também, a relevância desta tese em termos práticos, uma vez que o modelo proposto pode ser adaptado e utilizado em diferentes cenários de sistemas de manufatura. Por meio deste modelo, é viabilizado uma programação preditiva-reativa, que ocorre de forma automática sem a intervenção do planejador, buscando manter a estabilidade na produção. No entanto, os planejadores e gerentes tem acesso as informações relevantes para o monitoramento e tomada de decisões necessárias. Ainda, o modelo pode promover mais competitividade para as empresas que estão passando pela transformação da quarta revolução industrial.

1.5 INEDITISMO

O planejamento e controle da produção desempenha um papel fundamental na conexão dos níveis estratégico e operacional, sendo que uma de suas principais atividades é a programação da produção (JEON; KIM, 2016). Os autores ainda comentam que, uma eficiente programação da produção pode auxiliar na conversão dos desejos do gerenciamento de negócios (expressos em um plano de médio prazo) em uma produção real de chão de fábrica (domínio do gerenciamento de processos). Desta forma, a realização de uma programação eficiente é um dos fatores de sucesso para os sistemas de manufatura modernos, visto que é uma atividade de extrema importância representando a ligação entre o planejamento e a produção no chão de fábrica (NGUYEN; MEI; ZHANG, 2017).

Estudos mais recentes como o dos autores Minguillon e Stricker (2020), apresentam um método preditivo-reativo robusto para a programação da produção, analisando a relação entre o aumento da robustez na programação preditiva e a capacidade de reprogramação. Primeiro, os autores desenvolveram um modelo de programação de restrições (*Constraint Programming,* CP) para realizar a programação preditiva não robusta. O objetivo dessa otimização é terminar todos os trabalhos o mais rápido possível, para que sejam gerados tempos de folga entre a conclusão do trabalho e suas datas de vencimento. Em seguida, uma medida de robustez adaptada ao cumprimento da data de vencimento é desenvolvida para determinar onde distribuir os tempos de folga de qual comprimento. Com isso, a programação preditiva robusta é gerada e importada para uma simulação de eventos discretos. Através da simulação, são gerados distúrbios nas máquinas e as informações de reprogramação são exportadas. Finalmente, utilizando o aprendizado por reforço (*reinforcement learning*), uma proposta de reprogramação reativa é gerada e enviada para a simulação continuar a programação até que ocorra uma próxima perturbação. Este método foi analisado considerando a troca média das operações e o atraso médio dos trabalhos. Como resultado, a troca média das operações não foi influenciada pelo aumento da robustez, porém o atraso médio apresentou um comportamento influenciável por essa medida, significando que pode melhorar a adesão às datas de vencimento.

O estudo de Tighazoui, Sauvey e Sauer (2021) investigou uma nova medida de desempenho para avaliar simultaneamente a eficiência da programação pelo tempo de espera ponderado total e a estabilidade da programação pelo desvio ponderado do tempo de conclusão. O problema estudado considera uma máquina paralela idêntica e reprogramações à medida que chegam novos trabalhos ao longo do tempo. Com base em uma estratégia preditiva-reativa, é desenvolvido um modelo de Programação Linear Inteira Mista (*Mixed Integer Linear Programming*, MILP), bem como uma metodologia iterativa para lidar com a programação reativa. Os resultados obtidos dessa investigação, mostraram que o critério de estabilidade pode gerar um efeito significativo na programação da produção, proporcionando melhores resultados quando considerado apenas o critério da eficiência. Além disso, esta proposta pode fornecer a cada etapa, uma programação ideal em resposta a uma interrupção causada pela chegada de um novo trabalho em máquinas paralelas idênticas. Porém, à medida que o número médio de trabalhos otimizados por iteração aumenta, a resolução MILP torna-se limitada.

Os autores Manzini, Demeulemeester e Urgo (2022) apresentaram uma abordagem de programação da produção preditiva-reativa em um ambiente *flow-shop*. O objetivo da abordagem é minimizar o tempo de conclusão para produzir um lote de peças idênticas e capaz de enfrentar a incerteza do processo. Utilizando a estratégia da programação preditiva-reativa, primeiro é fornecido uma programação de linha de base considerando a incerteza que afeta os tempos de processamento. Com o acontecimento da incerteza, a programação reativa é operada adaptando a programação preditiva para a duração real das operações. Esta abordagem foi implementada no MATLAB e os resultados apontaram que a proposta pode ser benéfica para diversos casos, especialmente para lidar com eventos extremos e raros, ou seja, quando o tempo de processamento de uma operação pode se desviar fortemente dos valores esperados.

Com relação a recentes estudos que buscam integrar dados de estoque com a programação da produção, o artigo de Hu *et al.* (2021) investigou um problema integrando estoque e programação da produção em uma indústria que lida com produtos perecíveis. O objetivo é encontrar uma programação ótima para minimizar a soma do custo de estoque e do custo de produção. Para isso, os autores desenvolveram um algoritmo híbrido ICA-VNS (*Imperialist Competition Algorithm-Variable Neighborhood Search*) o qual é capaz de evitar que a solução caia no ótimo local. Por meio de experimentos computacionais, os resultados mostraram que a proposta supera outros algoritmos tanto em eficácia quanto em eficiência.

O estudo de Suhartanto, García-Flores e Schutt (2021) apresentou uma estrutura para a integração de estoques de matérias-primas e produtos acabados com a programação de produção. Na construção dessa estrutura, os autores utilizaram a CP e o gerenciamento de estoque para resolver o problema combinado de programação reativa e gerenciamento de estoque. O modelo de produção adotado foi o problema de programação de projeto com restrição de recursos (*Resource-Constrained Project Scheduling Problem*) considerando três produtos acabados, quatro tipos de matérias-primas e uma política de estoque. Os resultados alcançados por meio de experimentos computacionais mostraram que, a estrutura proposta permite gerar informações aos operadores sobre as faltas de estoque esperadas e as taxas de consumo e produção. Com isso, possibilita-se o reabastecimento imediato de material, novos pedidos de matéria-prima e/ou alterações na programação.

Considerando estes estudos recentes, além da revisão da literatura apresentada no Capítulo 3 e também na fase final no Capítulo 4, o ineditismo e a originalidade desta tese comprovam-se através dos seguintes aspectos. Em primeiro lugar, esta pesquisa se concentra no campo da programação da produção com a integração de dados de estoque, tema que se destaca pela sua relevância atual, mas pouca pesquisa foi exibida. Em segundo lugar, a estratégia escolhida foi a programação preditiva-reativa, a qual é citada como uma estratégia de grande aplicabilidade nos ambientes industriais para reprogramar sistemas de manufatura dinâmicos. Assim, este estudo fornece uma estrutura factível para a sua implementação em sistemas de manufaturas reais, bem como oferece uma estrutura teórica sólida sobre a qual pesquisas futuras podem ser desenvolvidas. Em terceiro lugar, nenhum estudo anterior foi encontrado abordando a programação da produção preditiva-reativa baseada em dados de estoque. Conforme os estudos revisados, alguns lidaram com a programação preditiva-reativa, porém não eram estritamente voltados aos dados de estoque. Outros trabalhos abordaram dados de estoque, mas não adotaram a estratégia preditiva-reativa. Além disso, diferentes gatilhos (*triggers*) da programação reativa e KPI’s foram considerados.

Adicionalmente, a proposta desta tese utiliza duas diferentes ferramentas. Para gerar a programação preditiva, adotou-se uma técnica de aprendizado de máquina (*Machine Learning*, ML), as Redes Neurais Artificiais (*Artificial Neural Networks*, ANN) e para gerar a programação reativa, adotou-se o método da otimização baseada em simulação (*simulation-based optimization*, SBO). Até onde sabemos, nenhum trabalho anterior considerou essas duas ferramentas juntas para lidar com o contexto proposto.

Finalmente, o modelo considera a perspectiva da Indústria 4.0, sendo validado por meio de um estudo de caso em uma empresa brasileira, fomentando a competitividade das indústrias nacionais, além de contribuir para o debate da comunidade científica.

1.6 DELIMITAÇÕES DA TESE

Para que se possa alcançar os objetivos propostos, torna-se necessária uma delimitação da pesquisa. No entanto, é importante que se permita conhecer os aspectos fundamentais do tema, mas delineando a pesquisa para que se prevaleça o seu foco. Assim, algumas delimitações necessárias são descritas a seguir.

Inicialmente, o modelo proposto considerou a estratégia da programação da produção preditiva-reativa, em um ambiente dinâmico e com política híbrida, ou seja, periódica e quando ocorrem eventos. Adicionalmente, considerou-se a dinâmica da programação da produção em um ambiente *job-shop*, ou seja, as máquinas não estão dispostas na sequência das etapas de trabalho (como em um ambiente *flow-shop*). Em vez disso, o fluxo da peça está de acordo com o arranjo das máquinas. Nesse ambiente, tem-se uma maior dificuldade para a programação da produção, já que existe uma maior sensibilidade às pequenas mudanças.

Ainda, o estudo considera o nível operacional dentro de um sistema de manufatura, ou seja, não abrangeu relações com empresas fornecedoras e com clientes. Dessa forma, é importante salientar que, os resultados e conclusões desta pesquisa não podem ser aplicados criticamente em qualquer sistema de manufatura, sendo necessário a adaptação do modelo proposto aos diferentes cenários. Outro fato importante a ser mencionado, é que a pesquisa focou em avaliar eventos/perturbações na programação da produção devido à falta de matéria-prima. Logo, outros eventos que podem causar instabilidades nos sistemas de manufaturas não foram considerados.

1.7 ESTRUTURA DO TRABALHO

Esta tese está estruturada em sete capítulos. Este primeiro capítulo compreendeu a contextualização, definição do problema, objetivos a serem alcançados, justificativa e relevância da pesquisa, ineditismo, além das suas delimitações, de modo a suportar o desenvolvimento dos demais capítulos do estudo.

O Capítulo 2 apresenta a metodologia da pesquisa adotada nesta tese, a qual seguiu as diretrizes da Resolução 001/PPGEP/2018, de 11/07/2018 do Programa de Pós-Graduação em Engenharia de Produção (PPGEP). Esta Resolução prevê instruções para a elaboração da dissertação de mestrado ou tese de doutorado sob a forma de coletânea de artigos para a defesa no PPGEP da Universidade Federal de Santa Catarina (UFSC). Assim, baseada nesta Resolução, esta tese consiste na coleção de cinco artigos estruturados de forma a alcançar o objetivo principal deste estudo. Com isso, no Capítulo 2 são apresentados o enquadramento metodológico, que conecta cada um dos artigos no contexto da pesquisa e também o procedimento metodológico de cada uma das fases, classificando-as quanto à metodologia adotada.

Em relação a formatação, alguns aspectos específicos foram adotados:

- Conforme previsto na Resolução mencionada, os Capítulos 1, 2, 6 e 7 foram escritos na língua portuguesa e os Capítulos 3, 4 e 5 foram escritos na língua inglesa, por se tratar de artigos que foram publicados ou serão submetidos em periódicos internacionais;
- As referências, citações, figuras, gráficos e tabelas seguiram o formato da Associação Brasileira de Normas Técnicas (ABNT);
- As referências dos Capítulos 1, 2 e 6 estão inseridas após o Capítulo 7 em uma única lista de referências;
- As referências dos capítulos de língua inglesa estão inseridas após seus respectivos capítulos, uma vez que fazem parte do artigo elaborado;
- Quando necessário a inclusão de Apêndice, este também consta no fim do seu respectivo capítulo;
- As versões originais dos artigos que já foram publicados podem ser acessadas através do Identificador de Objeto Digital (*Digital Object Identifier*, DOI) disponível nos capítulos.

O Capítulo 3 apresenta a Fase 1 da coletânea. Esta fase contempla como resultado três artigos. O Artigo 1.1 expôs a proposta inicial do modelo conceitual, com o objetivo de integrar dados de estoque com a programação da produção. Em seguida, o Artigo 1.2 conduziu uma revisão sistemática da literatura (RSL), com o intuito de identificar quais são as principais técnicas de ML atualmente empregadas para realizar a programação da produção. Neste artigo, foram expostas as técnicas mais promissoras para a implementação nessa temática. Por fim, o Artigo 1.3 também conduziu uma RSL. Porém, de uma forma mais abrangente e aprofundada, buscou identificar as lacunas e as oportunidades de pesquisas sobre a integração de dados de estoque com a estratégia de programação da produção preditiva-reativa. Além disso, considerando os resultados dos Artigos 1.1 e 1.2, o Artigo 1.3 também apresenta a versão completa e atualizada do modelo conceitual, já com a definição das ferramentas a serem adotadas para solucionar o problema estudado.

O Capítulo 4 apresenta a Fase 2 (Artigo 2) da coletânea. Esta fase desenvolveu o modelo computacional para testar parte do modelo conceitual apresentado no Capítulo 3, referente a programação reativa utilizando a otimização baseada em simulação.

O Capítulo 5 apresenta a Fase 3 (Artigo 3) da coletânea. Nesta fase desenvolveu-se o modelo de simulação computacional completo. A programação preditiva é gerada utilizando o ML e a programação reativa é gerada utilizando o SBO. Para validar a proposta, foi realizado um estudo de caso com dados reais de uma empresa de manufatura.

O Capítulo 6 apresenta a discussão e síntese desta tese. Embora o resultado de cada fase (Capítulos 3 ao 5) inclua suas próprias discussões, ao adotar a apresentação desta tese de doutorado na forma de coletânea de artigos, é necessária uma discussão geral, sintetizando todo o trabalho. Assim, neste capítulo, a discussão é alinhada aos objetivos da tese e articulada de acordo com os resultados documentados nos artigos, além de apresentar as contribuições teóricas e práticas de toda a pesquisa.

Finalmente, no Capítulo 7 a conclusão é apresentada, trazendo o fechamento da tese com relação a questão de pesquisa respondida bem como os objetivos alcançados. Complementarmente, este capítulo também relata as oportunidades para pesquisas futuras.

CAPÍTULO 2
2 METODOLOGIA DA PESQUISA

Conforme mencionado no Capítulo 1, esta tese apresenta-se no formato da composição de coletânea de artigos, sendo composta por três fases, as quais consistem na solução do problema de pesquisa. O Quadro 1 apresenta o resumo das três fases da pesquisa, incluindo os métodos de pesquisas adotados, conforme Miguel (2012). Cabe salientar que, o objetivo de cada fase está alinhado com os objetivos específicos da pesquisa, sendo que cada fase foi relatada por meio de um artigo científico final.

Com relação ao procedimento metodológico, a pesquisa pode ser classificada segundo alguns critérios, sendo estes: a sua natureza, os objetivos, a abordagem, os procedimentos técnicos e os métodos adotados (SILVA; MENEZES, 2005). Como esta tese compreende três fases de desenvolvimento, a classificação da pesquisa pode variar conforme as suas características específicas. A Figura 1 ilustra as fases para a condução desta pesquisa, com a descrição das atividades desenvolvidas, bem como as saídas de cada fase. Conforme Silva e Menezes (2005), esta tese conduziu uma pesquisa que se classifica do ponto de vista de sua natureza como aplicada. Esta classificação justifica-se pelo fato de a pesquisa gerar conhecimentos para a aplicação prática, buscando solucionar o problema identificado através de um modelo para a programação da produção preditiva-reativa baseada em dados de estoque.

Quanto aos objetivos, esta pesquisa teve caráter exploratório, descritivo e explicativo. Conforme Andrade (2010), a pesquisa exploratória visa proporcionar maiores informações sobre o assunto em estudo, facilitar a delimitação do tema e direcionar a pesquisa que se deseja desenvolver. Assim, em um primeiro momento a pesquisa na Fase 1 foi exploratória, pois através da RSL foram investigadas as lacunas e oportunidades de pesquisas referentes ao tema principal. Além disso, a RSL sobre as principais técnicas de ML também auxiliou a autora na escolha da melhor técnica a ser adotada para a programação preditiva. Em um segundo momento, a pesquisa passou a ter um caráter descritivo. A pesquisa descritiva é aquela que busca verificar se existe relações entre variáveis (GIL, 2010). Neste contexto, a construção e proposta do modelo conceitual, buscou integrar e conectar os dados de estoque com a estratégia da programação da produção preditiva-reativa. Com isso, foi possível entender as relações e interações no modelo conceitual proposto e gerar uma solução teórica otimizada para o problema.

Quadro 1 – Enquadramento metodológico

		OBJETIVOS	QUESTÃO DE PESQUISA	MÉTODO DE PESQUISA
FASE 1	Artigo 1.1	- Propor um modelo conceitual para a programação da produção preditiva-reativa orientada a dados de estoque	(*i*) Qual modelo de programação da produção preditiva-reativa seria adequado para considerar os dados de estoques?	Pesquisa Teórica Qualitativa 1. Modelo conceitual
	Artigo 1.2	- Identificar na literatura as principais técnicas de *machine learning* para viabilizar a programação preditiva	(*i*) Quais as técnicas de *machine learning* mais utilizadas para a programação da produção?	Pesquisa Teórica Qualitativa 1. Revisão da Literatura
	Artigo 1.3	- Identificar na literatura as principais abordagens referentes a programação da produção preditiva-reativa - Identificar os principais métodos inerentes à sua implementação	(*i*) Quais são os estudos que adotaram a estratégia de programação de produção preditiva-reativa? (*ii*) Quais são os estudos que abordaram a programação da produção baseada em estoque? (*iii*) Como as estratégias de programação da produção têm sido aplicadas?	Pesquisa Teórica Qualitativa 1. Revisão da Literatura
FASE 2	Artigo 2	- Validar o método da otimização baseada em simulação para gerar a programação reativa	(*i*) Como realizar a programação da produção reativa orientada a dados de estoque e qual o seu desempenho operacional?	Modelagem e Simulação Quantitativa 1. Modelo computacional 2. Caso teste
FASE 3	Artigo 3	- Mensurar o desempenho operacional do modelo desenvolvido por meio de simulação computacional, considerando um cenário real de uma empresa de manufatura	(*ii*) Qual o impacto operacional do modelo proposto para os sistemas de manufatura?	Modelagem e Simulação Quantitativa 1. Coleta de dados 2. Estudo de caso 3. Prospecção de cenários

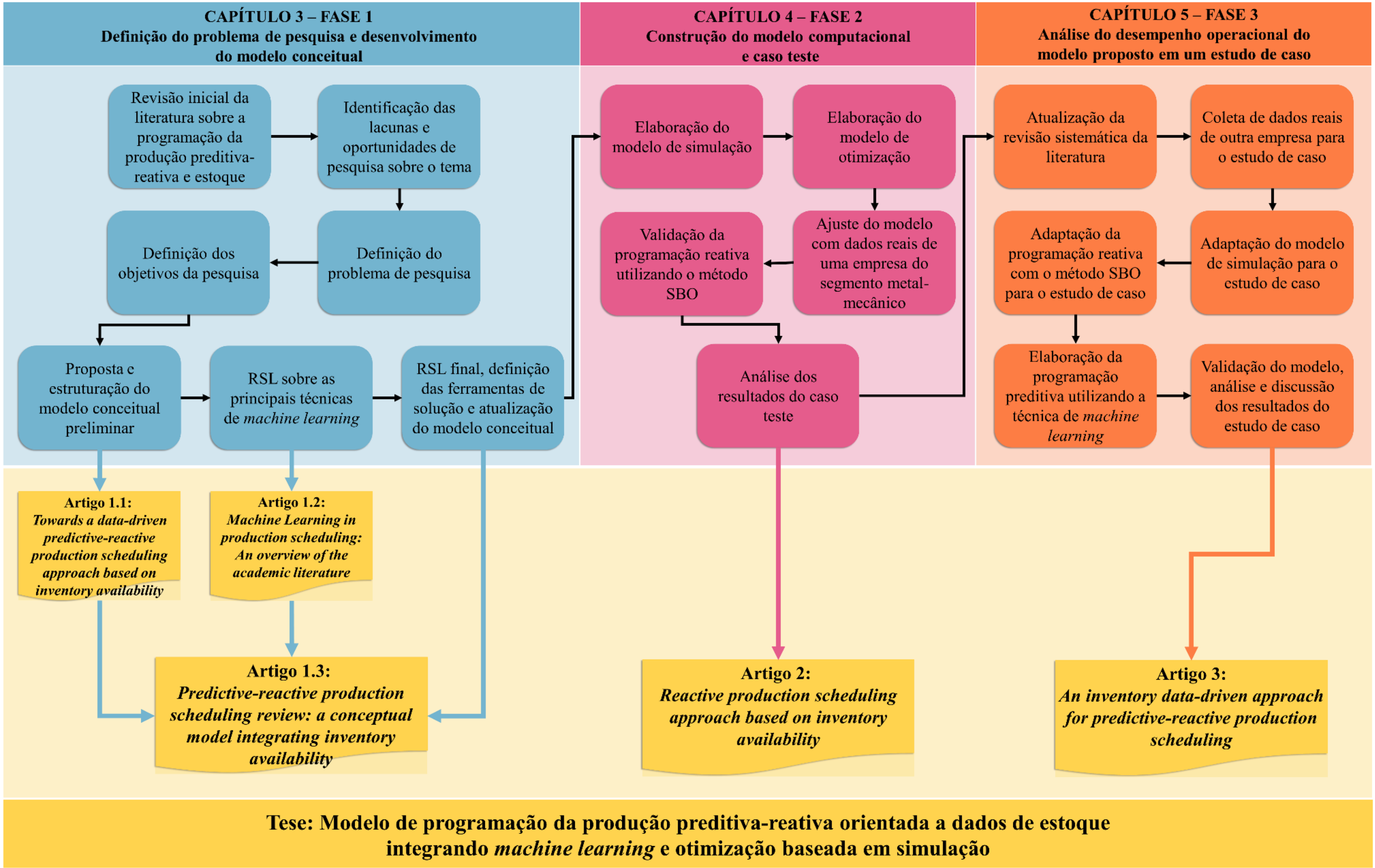
Fonte: Elaborado pela autora (2022).

Já na Fase 2, a pesquisa teve um caráter explicativo. As pesquisas explicativas buscam reconhecer quais elementos ocasionam o fenômeno analisado (GIL, 2010). Dessa forma, nesta fase foi identificado como integrar os dados de disponibilidade de estoque com a programação da produção, elemento este que impacta diretamente na estabilidade da programação. Assim, através da definição da lógica de monitoramento de estoque, foi possível integrá-la com a programação da produção e responder às rupturas do sistema. Por fim, na Fase 3, a pesquisa inicialmente teve um caráter exploratório, onde conduziu-se uma atualização da RSL, com o intuito de investigar novas abordagens na literatura entre os períodos de 2019 a agosto de 2021. Esta exploração novamente da literatura fez-se necessário para a verificação de possíveis estudos similares, de forma a manter o ineditismo e originalidade da tese. Após isso, a pesquisa passou a ter um caráter descritivo, uma vez que foi apresentado todo o modelo proposto, incluindo as ferramentas utilizadas para a programação preditiva e a programação reativa. Adicionalmente, estabeleceu-se as relações entre as programações e o sistema de manufatura estudado, bem como todas as variáveis envolvidas. Finalmente, a pesquisa classifica-se também como explicativa, pois esta exige um maior grau de complexidade e nesta Fase 3, apresentou-se o resultado final da proposta da tese, abrangendo todas as etapas das Fases 1 e 2 e suas complexidades.

Com relação a abordagem do problema, essa tese classifica-se como qualitativa e quantitativa. A Fase 1 é caracterizada como qualitativa, pois os resultados são originados a partir da interpretação da revisão de literatura (GIL, 2010). Na Fase 2, a abordagem do problema é caracterizada como quantitativa, uma vez que trabalhou com dados numéricos os quais foram analisados por meio de simulação computacional. Para Appolinário (2006), a pesquisa quantitativa centra-se na objetividade, buscando traduzir tudo aquilo que pode ser quantificável através da mensuração de variáveis predeterminadas, as quais deseja-se verificar e explicar sua influência sobre outras variáveis. Por fim, a Fase 3, assumiu características de pesquisa quali-quantitativa, ou seja, em um primeiro momento há uma interpretação da RSL conduzida e, após isso, ocorre a validação do modelo proposto por meio de simulação computacional.

No que diz respeito aos procedimentos técnicos adotados, esta tese explorou os procedimentos: (*i*) bibliográfico; (*ii*) documental e (*iii*) estudo de caso (SILVA; MENEZES, 2005). Na Fase 1, tem-se uma pesquisa predominantemente bibliográfica, uma vez que foi resultante da análise de estudos já publicados na literatura. Na Fase 2, utilizou-se a pesquisa documental, pois houve a consulta dos dados da empresa estudada para o caso teste. Já na Fase 3 adotou-se os três tipos de procedimentos. O procedimento (*i*) ocorreu com a análise de estudos já publicados na literatura. O procedimento (*ii*) sucedeu-se pela coleta de dados em uma outra empresa. O contato da autora com a empresa, aconteceu entre o período de maio a outubro de 2021 através da troca de *e-mails* e também por videoconferências, uma vez que devido a pandemia da COVID-19 (*Corona Virus Disease*), não foi possível realizar visitas presenciais a fábrica. Ainda, esta última fase também adotou o procedimento técnico (*iii*), já que o modelo proposto foi ilustrado em uma empresa do setor metal-mecânico. Para Gil (2010), um estudo de caso visa explorar situações da vida real ainda não-definidas, preservar o caráter unitário do objeto estudado, escrever a situação do contexto em que está sendo feita a investigação, além de explicar as variáveis causais do fenômeno em situações complexas. Finalmente, conforme definido por Miguel (2012) os métodos adotados nesta tese foram: teórico/conceitual na Fase 1 e simulação nas Fases 2 e 3.

Figura 1 – Procedimento metodológico da tese



Fonte: Elaborada pela autora (2022).

CAPÍTULO 3
3 FASE 1

Neste Capítulo serão apresentados os estudos que compuseram a Fase 1 desta tese, com o objetivo de definir o problema de pesquisa e desenvolver um modelo conceitual.

3.1 TOWARDS A DATA-DRIVEN PREDICTIVE-REACTIVE PRODUCTION SCHEDULING APPROACH BASED ON INVENTORY AVAILABILITY

Esta subseção apresenta o Artigo[1] 1.1, o qual foi publicado no *IFAC-PapersOnLine*. O artigo original publicado está disponível em: https://doi.org/10.1016/j.ifacol.2019.11.385.

Abstract: To survive in a competitive business environment, manufacturing systems require the proper deployment of advanced technologies coming from Industry 4.0. These technologies allow access to quasi-real-time data that provide a continuously updated picture of the production system, including the state of available inventory. Data-driven predictive-reactive production scheduling has the potential to support the anticipation and prompt reaction to overcome different kinds of disruptions that occur in production execution nowadays. This research paper aims to propose a conceptual model for a data-driven predictive-reactive production scheduling approach combining machine learning and simulation-based optimization, considering current inventory of raw material, work in process and final products inventory to characterize a job-shop production execution state. The approach supports decision-making in dynamic situations related to inventory availability that can affect production schedules.
Keywords: Predictive-reactive scheduling, manufacturing system, data-driven, machine learning, simulation-based optimization.

3.1.1 Introduction

Most manufacturing systems operate in dynamic environments where usually inevitable unpredictable real-time events may cause a change in the scheduled plans, and a previously feasible schedule may turn infeasible when it is released to the shop floor (OUELHADJ; PETROVIC, 2009; SOBASZEK; GOLA; ŚWIĆ, 2018). The strive for efficiency of production processes requires it to be planned and prepared before execution. Production scheduling is a vital solution that addresses some production-related problems (SOBASZEK; GOLA, 2015).

[1] BERGER, S. L. T.; ZANELLA, R. M.; FRAZZON, E. M. Towards a data-driven predictive-reactive production scheduling approach based on inventory availability. IFAC-PapersOnLine, 52, n. 13, p. 1343-1348, 2019.

There are numerous factors, referred to as uncertainty factors, which discard the production schedule immediately after the production process is initiated. Consequently, leading to disorganisation and production interruptions (KUNGWALSONG; KACHITVICHYANUKUL, 2006). The analysis of production processes allows specifying several sources of uncertainty, such as machine availability, time and availability of transportation, operation processing time, availability of personnel and tools, preparation times and due dates, as well as the availability of materials and semi-finished product (BILLAUT; MOUKRIM; SANLAVILLE, 2008; KÜCK *et al.*, 2016a). The occurrence of this problem can result in decreased competitiveness and loss of the customer's trust, which is alarming for a company in highly competitive world (SOBASZEK; GOLA; ŚWIĆ, 2018).

Therefore, the need for research into the consequences of potential disruptions emerges, in order to achieve a method of stability of executed processes. In this sense, many types of research have approached predictive-reactive scheduling, since it is one of the most common dynamic scheduling approach used in manufacturing systems (GOMES; BARBOSA-PÓVOA; NOVAIS, 2013; MEZIANE; TAGHEZOUT, 2018; VALLEDOR *et al.*, 2018). Predictive-reactive scheduling is a scheduling/rescheduling process in which schedules are adjusted in response to real-time events (OUELHADJ; PETROVIC, 2009). For scheduling to be able to respond to real-time data, it is necessary to increase automation and flexibility of manufacturing systems. Thus, allowing to take measurements to adapt production systems, implementing innovative and intelligent technologies as well as effective planning tools (KRENCZYK *et al.*, 2017).

Many researchers found solutions for designing and optimising production jobs schedules related to machine failure (BARTÁK; VLK, 2015; BUDDALA; MAHAPATRA, 2018; NOUIRI *et al.*, 2017). However, there is a lack of research that considers the current state of the job-shop production execution along with current inventory of raw material, work in process and final products inventory for the production scheduling execution. Besides that, production scheduling is surrounded by limitations due to the dynamic nature of manufacturing and the high mathematical complexity of scheduling (SCHOLZ-REITER *et al.*, 2010). As a result, classical methods are highly ineffective when considering modern manufacturing enterprises (SOBASZEK; GOLA; ŚWIĆ, 2018).

Mcfarlane *et al.* (2003) and Zhong *et al.* (2017) comment that with the advent of Industry 4.0, the manufacturing environment became smarter, allowing machines to vary their behaviours in response to different situations and requirements based on past experiences and learning capabilities. Thus, with the increase of available information in the factory floor, the adoption of data fusion and machine learning methods to address specific industry needs and requirements is encouraged (MICHALSKI; CARBONELL; MITCHELL, 2013). In addition, manufacturing systems are influenced by a wide range of stochastic. In literature, it is suggested that complex stochastic problems can be solved by simulation-based optimization (SBO) (GE *et al.*, 2014; KÜCK *et al.*, 2016a; LIN; CHEN, 2015). SBO is a powerful tool for solving complex stochastic problems because of the insertion of a simulation model into the objective function of the optimization (KÜCK *et al.*, 2016b).

This research paper aims to propose a conceptual model for a data-driven predictive-reactive production scheduling approach combining machine learning and simulation-based optimization and considers the current state of the job-shop production execution along with current inventory of raw material, work in process and final products inventory. The approach aims to support decision-making in dynamic situations related to inventory availability that can affect production schedules. This paper is structured as follows: In section 3.1.2 the literature review is presented to support the research. In 3.1.3 section addresses the proposed conceptual model. Finally, in section 3.1.4, the final considerations of the research are exposed.

3.1.2 Literature review

3.1.2.1 Predictive-Reactive Scheduling

Predictive-reactive approaches are often referred to as risk supported (CHAARI *et al.*, 2014). Predictive-reactive scheduling has two primary steps. The first step generates a production schedule. The second step updates the schedule in response to a disruption or the other event to minimize its impact on system performance (VIEIRA; HERRMANN; LIN, 2003).

Paprocka e Skołud (2017) commented that a predictive schedule has two functions. The first function relates to the allocation of jobs to resources in order to optimize one or more objective functions. The second function is to serve as an overall plan under the conditions of external disturbances. The predictive schedule is built based on statistical knowledge of uncertainty, aiming at determining a schedule that has a satisfying average performance. A precomputed schedule or a predetermined schedule, called a preschedule or predictive schedule, is generated and executed until a disturbance occurs. After that, a rescheduling procedure is launched to handle the disturbances (NOUIRI *et al.*, 2017).

Reactive scheduling refers to the schedule modifications that had to be made during project execution. The use of a baseline schedule in combination with reactive scheduling methods is referred to as predictive-reactive scheduling, which dispatches activities on-line or real-time (FRAZZON *et al.*, 2015; HERROELEN; LEUS, 2004). For Chaari *et al.* (2014) and Sobaszek, Gola e Świć (2018) the predictive-reactive approaches could be split into two phases. In the first phase, predictive scheduling is connected with the planning stage, known as off-line scheduling. Thus, in this stage, the nominal schedule (based on actual parameters of a system) and the predictive schedule (taking into account uncertainty and flexibility of the executed process) are developed. In the predictive scheduling, the events are considered to be predictable. For example, the jobs which are to be scheduled are all available initially, process times are known and deterministic, and machines and other resources are available throughout the scheduling horizon.

During the second phase, this schedule is used and adapted online. The schedule is created or modified in production. Changes in the process result in the implementation of an alternative schedule, called reactive scheduling. The on-line phase requires making scheduling decisions one at a time during the execution of the schedule. These decisions are then adapted considering the real time to take disturbances into account (COWLING; OUELHADJ; PETROVIC, 2004).

Predictive and reactive scheduling are applied to various scheduling problems, such as single machine scheduling problem (GOREN; SABUNCUOGLU, 2008; LIU; GU; XI, 2007), flow shop, job shop (AL-HINAI; ELMEKKAWY, 2011; HASAN; SARKER; ESSAM, 2011; PAPROCKA *et al.*, 2014), general shop and parallel machines (DUENAS; PETROVIC, 2008; TURKCAN; AKTURK; STORER, 2009).

However, there is still a gap in the literature regarding surveys that consider data from the shop floor like to the current inventory of raw material, work in process and final products inventory that indicate problems during the execution of the production schedule. Therefore, the predictive-reactive scheduling aims at minimising the effect of disruptions in the process that is being executed, ensuring that no loss of performance occurs in the presence of disruption.

3.1.2.2 Machine learning as part of data analytics

In recent years, it has been observed that the manufacturing systems are not able to remain unchanged, but only sporadic small adjustments are made. Yet, it is necessary to adapt systems to steadily changing conditions and not only clean environments. This need started to take into consideration the “complexity” of such systems. Nevertheless, the complexity analysis is challenging. It essentially consists of finding relations between factors (characteristics of complexity) using large amounts of data. Besides, it is necessary to remember that every enterprise has a different situation making this solution continuously changing (COLANGELO; KRÖGER; BAUERNHANSL, 2018).

Colangelo, Kröger e Bauernhansl (2018) comment that the focus of data analytics, supported mainly by data mining and machine learning, is to understand the underlying situation by processing the available data (data-driven approach). The usage of data analytics to replace current formulas is then necessary to be able to work under production conditions of high complexity. In this sense, approaches using machine learning algorithms recently gained importance. Machine learning algorithms are considered algorithms that are not programmed explicitly with an exact deterministic procedure. Moreover, machine learning algorithms are named data-driven approaches because the input data affects the performance and procedure to a large extent (STRICKER *et al.*, 2018).

However, machine learning is not a favourable method for all industrial problems. Russell e Norvig (2016) commented that the following properties are deemed advantageous for machine learning algorithms: (*i*) applications with a limited scope in terms of dimensions of states and actions (the learning period is dependent on these dimensions), (*ii*) fast responsive real-time decision systems (computing the output of a machine learning algorithm requires just linear operations), (*iii*) “cheap” training data (the trial-and-error approach is intensively data-driven) and (*iv*) complex environments that can hardly be described in detail (ability to generalize).

Thus, data analytics through advanced machine learning techniques has led to a vast and diverse set of useful applications that affect daily lives. The ability of the algorithm to learn complex relationships between the attributes of the data and the target values offer support to find trends and symptoms of failures in order to carry out tasks optimally (CHO *et al.*, 2018). Therefore, in the manufacturing system context, Nemirovsky *et al.* (2018) recommended that researches using machine learning may be a fruitful option to improve scheduling. Besides that, Morariu e Borangiu (2018) commented that future works could be focused on collecting larger data sets from real shop floor resources and on better understanding the patterns within these data sets.

3.1.2.3 Simulation and Optimization in Manufacturing Systems

Simulation models can explicitly represent the variability, interconnectivity and complexity of a system. As a result, it is possible with a simulation to predict system performance, compare alternative system models, and determine the effect of alternative policies on system performance (ROBINSON, 2004). The discrete-event simulation model is a simplified representation of a system developed to understand its performance over time and to identify potential means of improvement (TAKO; ROBINSON, 2010). In this model, the state variables change only at those discrete points in time at which events occur. Entities may compete for system resources, possibly joining queues while waiting for an available resource (FRAZZON *et al.*, 2014).

However, the simulation cannot guarantee the optimization of these systems concerning performance indicators (FRAZZON *et al.*, 2015). Therefore, optimization methods are mainly used if a complex system can be modelled by a simplifying abstraction (KÜCK *et al.*, 2016b). Nevertheless, optimization methods possess limitations to evaluate the impact of uncertainty, either because it becomes too complicated or due to high computational resources (FRAZZON; ALBRECHT; HURTADO, 2016). Thus, Kück *et al.* (2016b) still comment that a promising approach with the aim of combining the strengths of both is the so-called simulation-based optimization (SBO). This approach is suitable for solving dynamic optimization problems such as the scheduling of manufacturing systems.

In the context of simulation, Chong, Sivakumar e Gay (2003) proposed a simulation-based real-time scheduling mechanism for dynamic discrete manufacturing. Krenczyk *et al.* (2017) developed an integrated software module that allows fast simulation model generation and conducts simulation experiments for rapid analysis of the prepared schedule. It regards the available quantity and the capacity of the material handling vehicles, the timetables, and the location and capacity of the material handling systems. In the optimization field, Jang *et al.* (2013) developed a predictive model control using an optimization-based that allows the scheduler to both solve the constraint-aware production optimization and the in-process inventory control problem at each scheduling instance. Nouiri *et al.* (2017) propose a two-stage particle swarm optimization to solve flexible job shop scheduling problems under machine breakdowns. Accordingly, it was possible to identify the lack of research that joined simulation and optimization to predictive-reactive scheduling in a smart manufacturing environment.

3.1.3 Proposed conceptual model

In this section, the conceptual model for predictive-reactive production scheduling considering inventory data from the shop floor is proposed. As shown in Figure 2, the main elements of the proposed conceptual model are data analytics with machine learning to generate predictive schedules and reactive schedules. The entire system is based on data obtained in the execution of production processes, especially the inventory data from the shop floor. Therefore, this model results in feedback. Data acquisition is carried throughout input data from the ERP system, demand forecasting, demand capacity and other necessary information to generate the scheduling.

In the first step, data analytics with machine learning provides support to generate predictive scheduling. The data will be analyzed mainly considering the inventory of raw material, work in process and final products inventory. Problems may occur, for example, due to the poor quality of the material of the raw material inventory, which can affect the quality of the work in process and also the final products generating repairs; due to the lack of raw materials, material in the process or final products backlogs. After being properly selected and processed with statistical tools, the data enables disruption prediction and ensures robustness of the schedule by identifying what can affect the production schedule. The data employed at this step are statistical and predominantly consist of historical information concerned with analysed disruptions.

In the second step, simulation-based optimization with machine learning is responsible for creating reactive scheduling. This system includes a database of uncertainty factors and historical data of scheduling problems (poor quality materials, materials that were missing during the execution, availability inventories, past consequences of rescheduling, optimal schedules, the lateness of jobs, etc.). It also employs machine learning and grants decisions based on current and historical data. A database is structured with the data from the shop floor, considering especially the data related to the inventories and the problems that may occur with these inventories, as already mentioned in the predictive scheduling. This will allow the system to counteract to particular disturbances with appropriate actions, generating new reactive scheduling. So, the reactive scheduling is characterised by dynamic data acquisition, inference and a new production scheduling for execution.

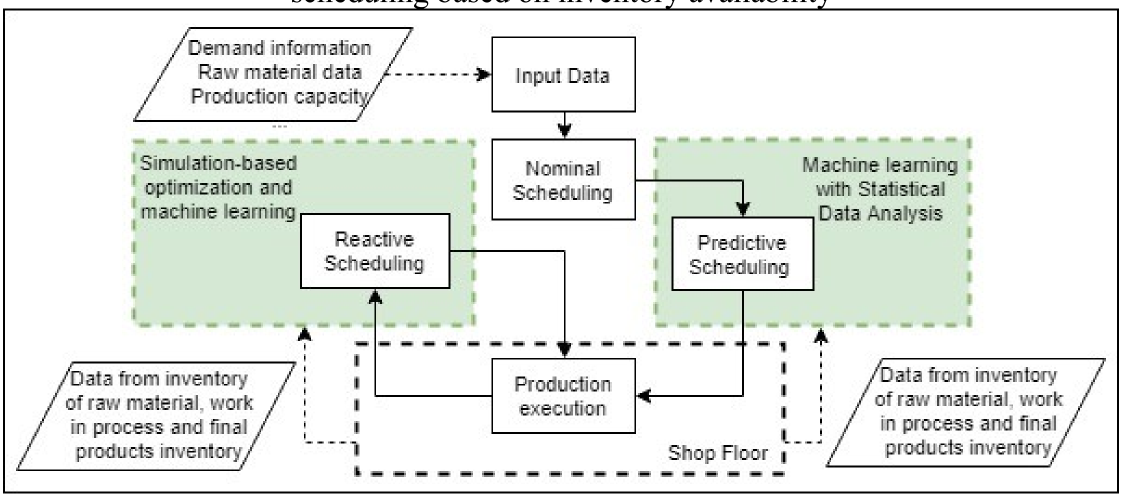
In order to develop the described model, the integration of machine learning and simulation-based optimization is proposed. This integration will occur during the communication between the machine learning software and the simulation software. Firstly, only the simulation will be used without the optimization. Enabling the simulation software to collect the input data and the nominal scheduling, according to the regular company schedule. Then, the machine learning software verifies through a statistical data analysis the historical information and the off-line data. This analysis concerned with disruptions related to inventory of raw material, work-in-process and final products inventory which was not considered in the nominal scheduling and generates the predictive scheduling in order to eliminate disruptions.

During the production execution, the data related to the interruptions of production lines are stored, and the system also verifies the same problems due to the inventory of raw material, work-in-process and final products inventory. If those problems occur, it is verified if they affect the current schedule and if so, this data is sent to the system, and reactive scheduling is triggered.

During this analysis, the simulation-based optimization will be used. For the reactive scheduling, the machine learning software collects online data from the shop floor. This data is referring to the inventories. While it is generating a solution, the simulation software evaluates partial solutions and returns the results to the first software. This process occurs until the stop criteria is satisfied to generate optimized reactive scheduling to be executed.

Thus, this conceptual model proposes data-driven predictive-reactive scheduling from the shop floor. The proposed approach enables the generation of predictive-reactive scheduling in order to prevent error inheritance that might result from discrepancies between the developed model schedule and the real production process.

Figura 2 – The proposed conceptual model for data-driven predictive-reactive production scheduling based on inventory availability



Fonte: Elaborada pelos autores (2019).

3.1.3.1 Discussions about the conceptual model

Production scheduling is one of the main problems in production planning and control, and is the main part of the performance of manufacturing organizations. Although production scheduling does not seem so complicated, there are several uncertainty factors that discard the schedule immediately after the production process initiated, which can lead to system disorganization (CHAN; AU; CHAN, 2006).

Traditionally, methods have been developed to design and optimize production jobs schedules. Janak *et al.* (2006) presented a reactive scheduling framework which provides an immediate response to unexpected events such as equipment breakdown or the addition or modification of orders. For that, the proposed mathematical framework utilizes a MILP mathematical framework developed for short-term scheduling problems with modifications introduced to reflect the effects of the unforeseen event. Pan, Liao e Xi (2012) proposed an integrated prognostics-based-scheduling model incorporating both production scheduling and predictive maintenance planning for a single machine with the objective of minimizing the maximum tardiness. Predictive maintenance operations are performed based on a new metric called Remaining Maintenance Life (RML). Thus, this model can enable a collaborative machine life cycle management, which helps predict RML information throughout machine's deterioration process. Ladj, Varnier e Tayeb (2016) proposed a genetic algorithm with the objective of minimize the total interventions cost on a single machine subjected to predictive maintenance.

Even if there are efficient analytical solver methods to perform the production scheduling, the proposed solutions for designing and optimising production jobs schedules are burdened with limitations due to dynamic nature of manufacturing and high mathematical complexity of scheduling. In the context of Industry 4.0 the generation of large amounts of data in modern manufacturing systems represents a source of knowledge for manufacturers and can lead to savings and improvements. However, the potential present in these data is insufficiently exploited (MANNS; WALLIS; DEUSE, 2015). So, the machine learning could improve production scheduling robustness since knowledge included in data may help to handle predictable and unpredictable events.

Sobaszek, Gola e Świć (2018) proposed a solution to job-shop scheduling, integrating predictive and reactive scheduling, which is essentially an intelligent process of job scheduling optimisation exhibiting features of machine learning. The process is based on a robust schedule that derives from actual historical data of machine failure or technological operation processing times. Hammami; Mouelhi e Said (2015) proposed the Artificial Neural Networks (ANNs) as a learning based method to integrate intelligent behaviors into the agents. The objective is to obtain efficient scheduling results through a simultaneous exploitation of agents' communication and neural networks' learning capabilities for the preparation of a cooperative adaptable online resolution schedule. Ji e Wang (2017) present a big data analytics based fault prediction approach for shop floor scheduling. Based on the available data on the shop floor, the potential fault/error patterns, referring to machining errors, machine faults and maintenance states, are mined for unsuitable scheduling arrangements before machining as well as upcoming errors during machining. So, the potential faults can be predicted ahead of task machining, and before fault happening during machining.

Although the recent literature presents some research related to the use of machine learning techniques applied in the production scheduling environment, there have not been found any research that considers inventory data from the shop floor to perform production scheduling. Thus, the proposed conceptual model aims to approach a data-driven predictive-reactive production scheduling combining machine learning and simulation-based optimization, considering the current state of the job-shop production execution along with current inventory of raw material, work in process and final products inventory. In fact, data sources represent an important aspect at the core of machine learning, because the meaningfulness of the results greatly depends on the quality and source of the data used to train the models. So, a relevant and differential aspect about the development of this research is the use of inventory data to perform the predictive-reactive production scheduling, which has not been considered in previous studies.

3.1.4 Conclusions

Advances in Industry 4.0 open an efficient way to innovate strategies in smart manufacturing environments, and these advanced technologies generate industrial big data. In this sense, classical production scheduling methods are highly ineffective considering actual manufacturing enterprises. This is because existing solutions for designing and optimising production jobs schedules are burdened with limitations due to the dynamic nature of manufacturing and the high mathematical complexity of scheduling. So, to exploit this large amount of data and the complex environment of the manufacturing, new approaches to production scheduling became indispensable for an effective organisation and management of any production process.

In this context, a new conceptual model for predictive-reactive scheduling combining machine learning and data-driven simulation-based optimization considering inventory availability was presented. A relevant part of the conceptual model is the integration of machine learning and simulation-based optimization to generate reactive scheduling.

This proposal allows the data from shop floor to generate information by avoiding downtimes through predictive knowledge and also enables the reactive scheduling to generate an optimized rescheduling according to the disruptions that have occurred in the production execution. This approach minimizes the total cost and optimizes material usage. Thus, the reduction of the number of stops in the production due to problems that occurred with inventory of raw material, work in process and final products inventory, will help to ensure competitive advantage, avoiding unforeseen downtimes, which reduce productivity. Future research will focus on the development of the simulation model and the simulation-based optimization integrating the machine learning in order to materialize the conceptual model and to verify its efficiency when compared to other models presented in the literature.

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3.1.5 References

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3.2 MACHINE LEARNING IN PRODUCTION SCHEDULING: AN OVERVIEW OF THE ACADEMIC LITERATURE

Esta subseção apresenta o Artigo[2] 1.2, o qual foi publicado no *Dynamics in Logistics, International Conference on Dynamics in Logistics* (LDIC 2020). O artigo original publicado está disponível em: https://doi.org/10.1007/978-3-030-44783-0_39.

Abstract: Production scheduling is an important tool for a manufacturing system, where it can have a significant impact on the productivity of a production process. In this sense, the application of machine learning can be very fruitful in this field, since it is an enabling computer programs to automatically make intelligent decisions based on data to improve performance at the manufacturing system. Therefore, this paper aims to explore the use of machine learning in production scheduling under the Industry 4.0 context. A systematic literature review was conducted to identify the main machine learning techniques currently employed to improve production scheduling. As a result, bibliometric analysis evidenced the continuous growth of this research area and identified the main machine learning techniques applied. Finally, the gaps leading to further research are high-lighted.
Keywords: Machine Learning, Production Scheduling, Manufacturing System.

3.2.1 Introduction

In the modern world, manufacturing companies are increasingly gaining access to vast amounts of data from several sources (FLATH; STEIN, 2018). Extracting knowledge from this data holds great potential to improve and add value to production processes (MULRENNAN *et al*., 2018). This provides the foundation for the fourth industrial revolution, better known as "Industry 4.0".

In the production context, Industry 4.0 is defined as the intelligent flow of the work-pieces machine-by-machine in a factory, based on real-time communication between machines (LEYH; MARTIN; SCHÄFFER, 2017). In this sense, Peruzzini, Grandi e Pellicciari (2017) commented that Industry 4.0 intends to make manufacturing intelligent and adaptive using flexible and collaborative systems to solve problems and make the best decisions. Rüßmann *et al*. (2015) describe nine groups of technologies to enable the realization of Industry 4.0, which are: (*i*) Big Data and Analytics; (*ii*) Autonomous Robots; (*iii*) Simulation; (*iv*) Horizontal and Vertical System Integration; (*v*) Industrial Internet of Things; (*vi*) Cybersecurity; (*vii*) Cloud;

[2] TAKEDA-BERGER, S. L.; FRAZZON, E. M.; BRODA, E.; FREITAG, M. Machine Learning in Production Scheduling: An Overview of the Academic Literature. In: International Conference on Dynamics in Logistics. Springer, Cham, 2020. p. 409-419.

(*viii*) Additive Manufacturing and (*ix*) Augmented Reality. However, this paper focuses on Big Data Analytics (BDA), and more specifically on Machine Learning (ML) techniques applied in production scheduling. Production scheduling aims to accomplish the optimal sequence of tasks, optimally allocating limited resources to processing tasks over time (LI; IERAPETRITOU, 2008).

Several different approaches to address the problems of production scheduling have been found in the literature (LI; IERAPETRITOU, 2008). However, increasingly dynamic market conditions have spurred the development of new and modified methods for production scheduling, increasing the complexity of today's manufacturing environment (BALDEA; HARJUNKOSKI, 2014). Thus, to overcome some of today's significant challenges of complex manufacturing systems, machine learning techniques have been used. These data-driven approaches can find complex and non-linear patterns in data of different types and sources. Such data is transformed into relevant information that can support decision-makers or can be used automatically to improve the system (WUEST *et al*., 2016).

In this context, this paper aims to conduct a systematic literature review on the use of machine learning in production scheduling under the Industry 4.0 context. To this end, the research seeks to answer the following question: *What are the main machine learning techniques currently employed to perform production scheduling?*. The review was conducted on the scientific bases Web of Science and Scopus through a biblio-metric analysis to identify the main applied ML techniques and content analysis to identify future perspectives. This paper is structured as follows: In section 3.2.2, the systematic literature review methodology is described. The 3.2.3 section presents and analyzes the results of the literature review. In section 3.2.4, the main machine learning techniques are presented. Finally, in section 3.2.5, the final considerations of the research are exposed.

3.2.2 Research methodology

In this section, the process and methodology that was followed to conduct this study are presented. The systematic literature review was based on the guidelines established by Moher *et al*. (2009) and Tranfield, Denyer e Smart (2003). The research methodology was divided into three steps: (*i*) search and papers collection, (*ii*) papers screening, and (*iii*) results analysis.

In the first step, the search was performed in the Scopus and Web of Science databases. These databases are considered the largest repositories of scientific documents (GUERRERO-

BOTE; MOYA-ANEGÓN, 2012). For the search the keyword combinations were defined, according to Chart 2. The idea is to search for papers combining machine learning and scheduling for production approaches. Additional keywords have been tested, but they added many non-theme-related papers. Thus, the keywords used resulted in more appropriate documents, potentially including all papers for analysis. As delimitation of the search, only papers written in English and published in and after 2011 have been reviewed. This year delimitation was defined since the objective is to obtain an overview of the use of machine learning in production planning in the era of the fourth industrial revolution (ALCÁCER; CRUZ-MACHADO, 2019; KAGERMANN; LUKAS; WAHLSTER, 2011).

Quadro 2 – Keywords search

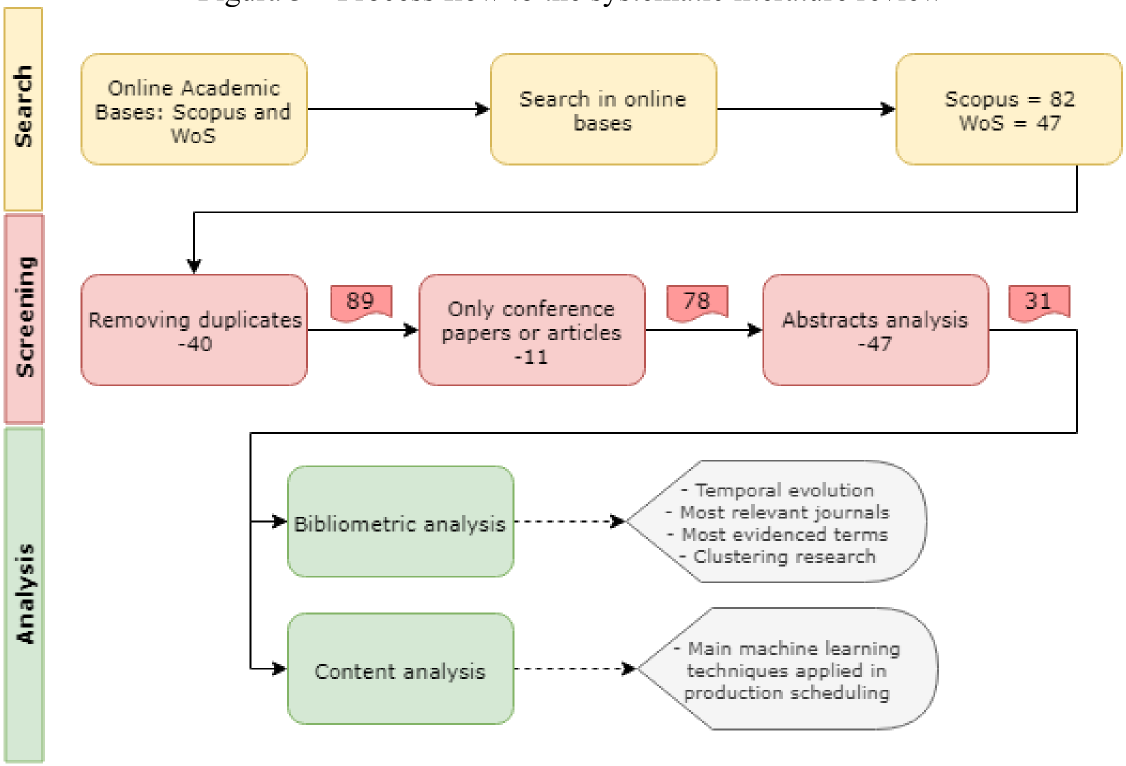
Databases	**Keywords**	**Results**
Scopus	TITLE-ABS-KEY (("machine learning") AND (“scheduling”) AND (“production”))	82
Web of Science	TS=((“machine learning”) AND (“scheduling”) AND (“production”))	47
Total		**129**

Fonte: Elaborado pelos autores (2020).

According to Chart 2, searching the databases resulted in 129 papers found. For step (*ii*), papers screening, first the duplicates were removed and afterwards criteria were established to select only papers relevant to the research, as follows: (a) only articles or conference papers; (b) analysis of abstracts to identify theme alignment; and (c) full text papers that can be accessed by CAPES *Portal de Periódicos*. After the completion of step (*ii*), the final portfolio was 31 papers.

It should be noted that the research was conducted in June 2019. The research protocol was built according to the process model presented in Figure 3, the main purpose of this study was to select only papers that are related to the adoption of machine learning techniques in the context of production scheduling.

Figura 3 – Process flow to the systematic literature review



Fonte: Elaborada pelos autores (2020).

Thus, with the final portfolio, it was possible to perform the third step, which will be presented in the next section. In the third step (*iii*), results analysis, a bibliometric analysis was performed to identify the main characteristics of the research area and content analysis to answer the research question of the study.

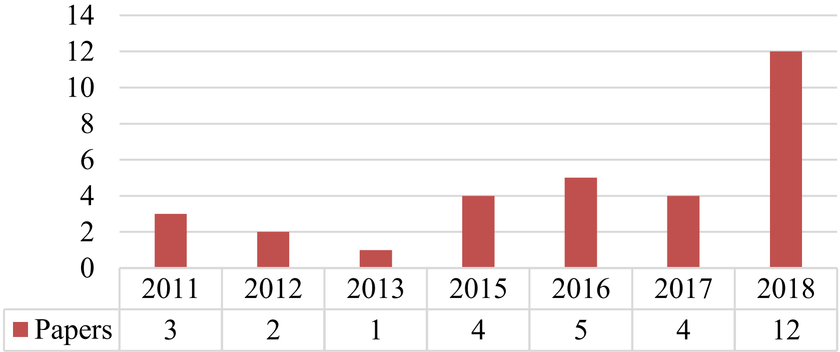
3.2.3 Bibliometric analysis of the portfolio

For the bibliometric analysis, the Bibliometrix tool was utilized, developed for performing comprehensive science mapping analysis. It was programmed in R, is open-source, and provides a wide variety of statistical and graphical techniques (ARIA; CUCCURULLO, 2017). The bibliometric analysis considered the portfolio of 31 papers to be evaluated according to the dimensions: publications temporal evolution, papers per journal, most cited papers, and highlighted keywords.

Figure 4 shows the year of publication of each of the papers that compose the portfolio. This filter is useful to compare the papers in different time slices tracing its historical evolution. As the portfolio is relatively small, these numbers just give an idea of the development, but in this case, it can be seen that there were few publications between 2011 and 2013, but from 2015 the number of publications has grown constantly, except for a small break in 2017. Between

2017 and 2018, publications increased by 300%. This analysis highlights the growing interest in applications of machine learning techniques in the production scheduling environment.

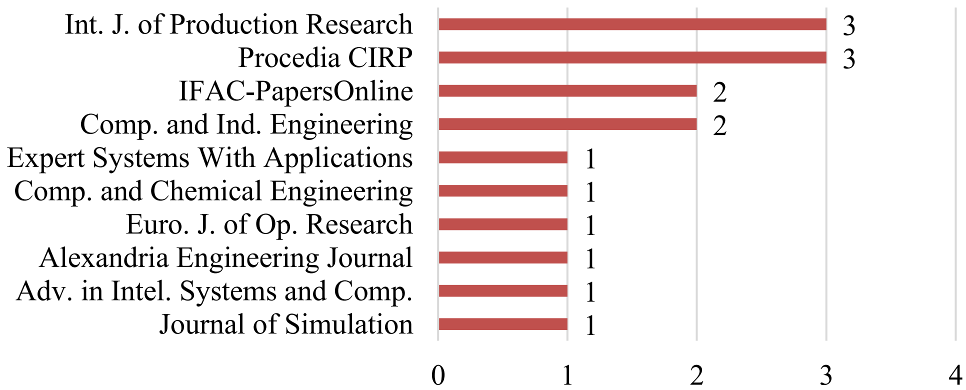
Figura 4 – Temporal evolution of publications



Fonte: Elaborada pelos autores (2020).

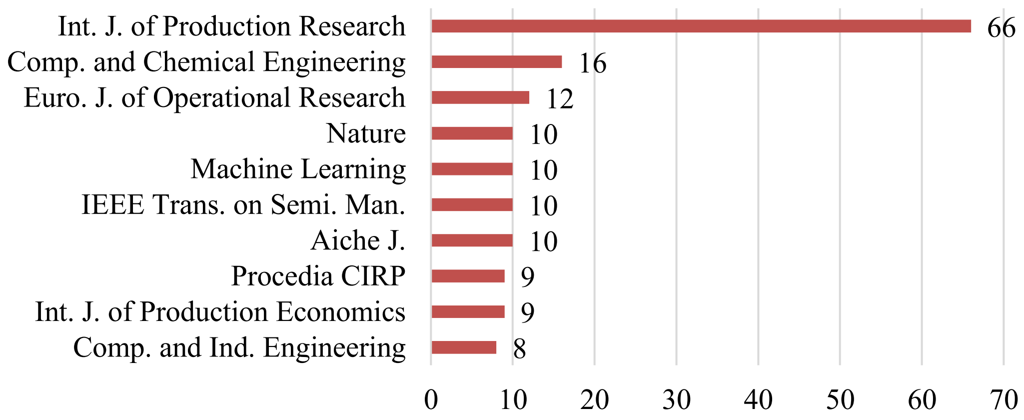
Figure 5 shows the ten journals with the highest concentration of publications in the analyzed portfolio. The International Journal of Production Research and Procedia CIRP contain the largest amount of published papers, followed by IFAC Papers Online and the Computers & Industrial Engineering journal. Figure 6 shows the top ten journals where papers, which have been cited by papers of the analyzed portfolio, have been published according to the Scopus database. In the International Journal of Production Research most of the citing papers have been published, followed by several other journals that link studies of operations management, engineering, and technology.

Figura 5 – Papers per journal



Fonte: Elaborada pelos autores (2020).

Figura 6 – Journals, in which papers have been published that have been cited by the 31 papers

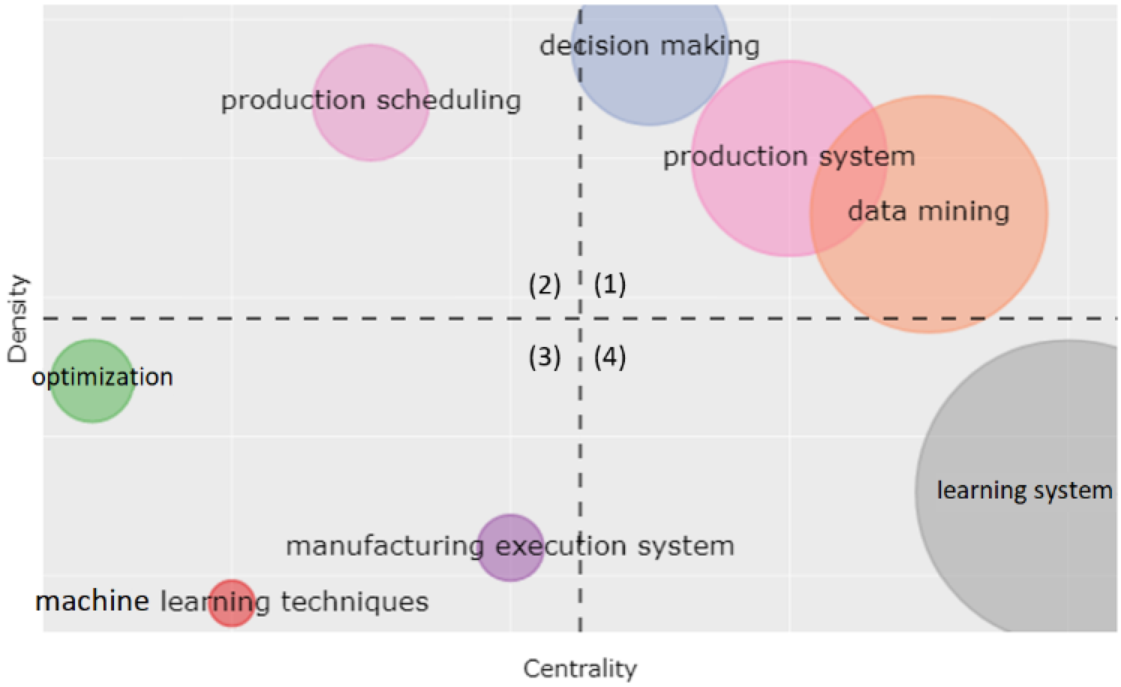


Fonte: Elaborada pelos autores (2020).

Figure 7 shows a thematic map considering the most evidenced terms in the keywords of the publications, relating the density and centrality of the terms from four perspectives, according to Cobo *et al*. (2011): (1) motor, (2) specialized, (3) emerging and (4) basic themes. The density can be read as a measure of the theme's development, and the centrality can be read as the importance of the theme in the entire research field (for more details see Cobo *et al*. (2011)). Each bubble represents a network cluster, i.e., the bubble name is the keywords, belonging in the cluster, with the higher occurrence value, the bubble size is proportional to the cluster keywords occurrences, and the bubble position is set according to the cluster centrality and density (Cobo *et al*., 2011).

The upper-right quadrant represents motor themes, i.e., they are well developed and important terms for the structuring of a research field, in this case "*decision making*", "*production system*" and "*data mining*" appear in this classification. Commonly, the motor-themes present strong centrality and high density. Thus, the placement of terms in this quadrant implies that they are related externally to concepts applicable to other themes that are closely related. The upper-left quadrant has themes with well-developed internal ties, in which case the term "production scheduling" appeared in this classification. However, in this quadrant the themes are very specialized and a little bit more peripheral in character.

Figura 7 – Thematic mapping of the area

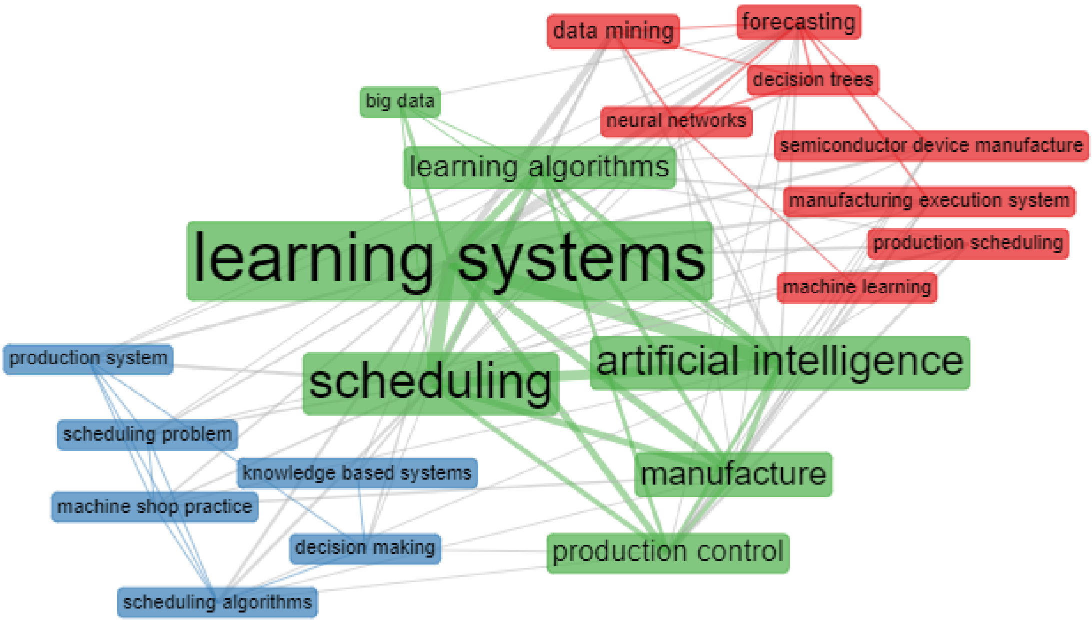


Fonte: Elaborada pelos autores (2020).

The terms "*optimization*", "*machine learning techniques*", and "*manufacturing execution system*" were classified in the lower-left quadrant, which presents themes are both weakly developed and marginal. The themes of this quadrant usually have low density and low centrality, i.e., are considered emerging, which need for further studies for development in these fields. Finally, in the lower-right quadrant are the basic themes, considered important for the development of the field, but not yet well developed. In this quadrant is the term "*learning system*", which more broadly considers aspects of studies that have adopted learning techniques for manufacturing systems. Due to bubble size it is possible to observe that this term had a lot of occurrences in the papers analyzed, highlighting its importance in research in this field.

Figure 8 shows a multi-dimensional scaling keywords co-occurrence network (HUANG; TZENG; ONG, 2005) using the walktrap clustering algorithm (PONS; LATAPY, 2005), generated automatically by Bibliometrix. With this map, it is possible to identify the most correlated clusters of terms and the intercession between the themes investigated in this re-search. In this sense, the analysis may occur as follows. The position of terms may indicate terms with more occurrence in articles (centrality) and terms with less occurrence (periphery). Just as the box size also indicates the most frequently occurring terms (larger boxes) and the least frequently occurring terms (smaller boxes). In addition, the line size is proportional to the co-relation of the terms, i.e., how stronger is the line, more related these words were in the papers.

Figura 8 – Keywords co-occurrence network



Fonte: Elaborada pelos autores (2020).

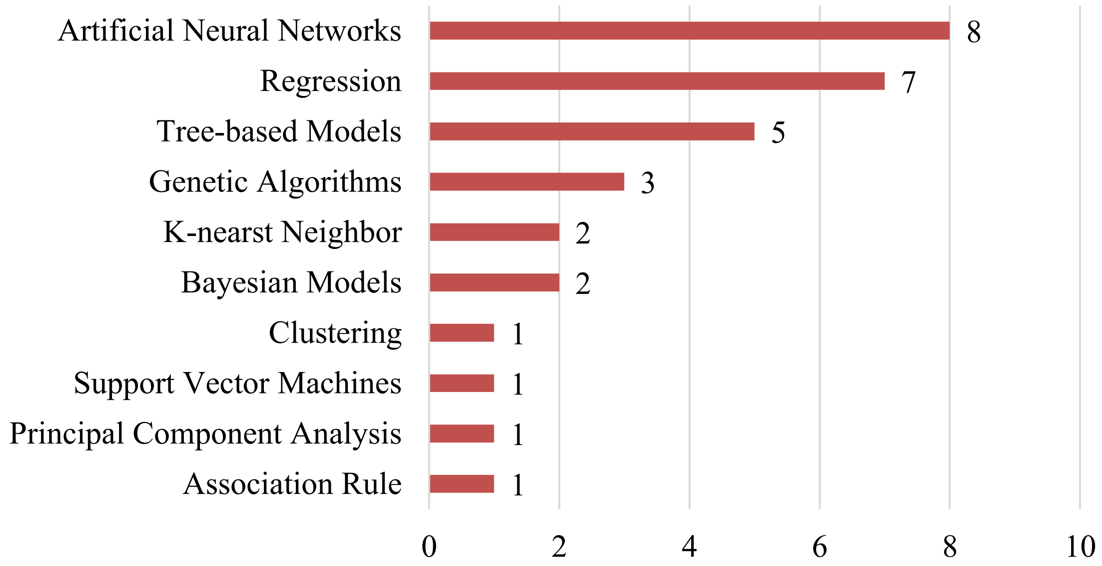
Three main clusters were formed in green, red, and blue. The green one presents the most frequent terms, due to the centrality of the words and the size of the boxes. Additionally, the words of this cluster are strongly correlated with each other, as they presented thick lines, such as "*learning system*", "*artificial intelligence*", and "*scheduling*". Furthermore, the words of this cluster also generate a vast connection to the red and blue clusters.

In summary, an analysis of the formed clusters can be performed. The red cluster includes the terms most related to the techniques adopted in the portfolio papers, such as neural networks, decision trees, machine learning. The blue cluster relates to application strategies, such as scheduling problems, production systems, decision making. Finally, the green cluster can be classified with terms related to innovation and Industry 4.0, such as learning systems, artificial intelligence, big data, learning algorithms.

3.2.4 Main machine learning techniques applied in production scheduling

In order to reply to the main question of this paper, Figure 9 shows the compiled numbers of uses of each machine learning technique family found in the selected papers of the portfolio. The formation of family groups was based on Marsland (2015) and Géron (2019). It is important to mention that, in the case of papers applying several technique families, only the best performing technique, according to the results presented by the authors of the papers, was counted.

Figura 9 – Machine Learning techniques families and their number of uses



Fonte: Elaborada pelos autores (2020).

This analysis shows that four techniques are most applied. These are Artificial Neural Networks, Regression, Tree-based models, and Genetic Algorithms. Artificial Neural Networks (ANNs) technique has widely been used in production scheduling (HEGER *et al.*, 2016). This technique can provide answers to inputs on an online system which seeks optimizations and acts faster than traditional heuristics which can take, hours, days or weeks to provide desirable results (GOMES *et al.*, 2017). Lee *et al.* (2018) proposed an architecture framework to implement the cyber-physical production systems cooperating with other manufacturing information systems for quality prediction and operation control in metal-casting processes. The authors used Decision Tree, the Random Forest Model, the ANNs model, and the Support Vector Machine model. Among them, the ANNs model showed the highest accuracy.

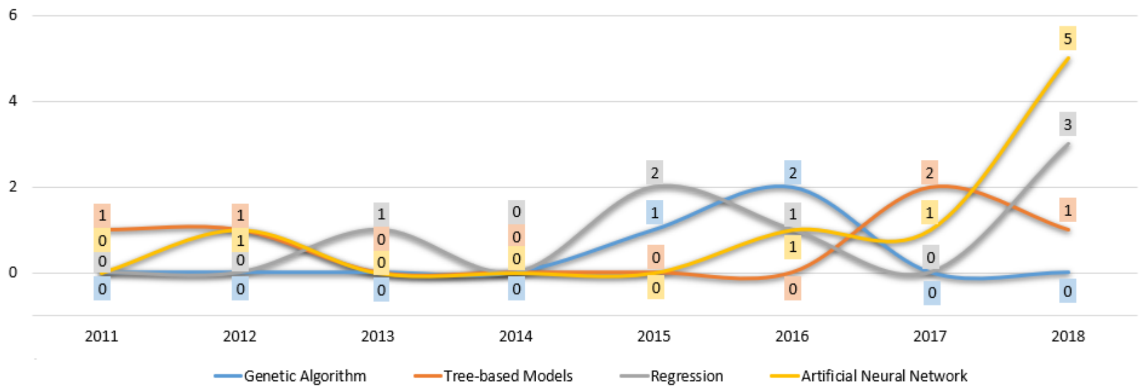
The second technique, Regression, also had a wide application in the portfolio's papers. This technique has a good prediction performance in comparison to other techniques. Additionally, the Regression method is used for forecasting and finding the causal relationship between variables (HEGER; HILDEBRANDT; SCHOLZ-REITER, 2013). Gaussier *et al.* (2015) studied how predictions of the running times may help in obtaining a better schedule. For this purpose, the authors used Regression method and cost functions that are used to learn the prediction model. The results showed an average gain of 28% compared to the classical EASY policy algorithm.

The third most applied technique were Tree-based models. These techniques are the most commonly known method when building decision models (BERGMANN; FELDKAMP;

STRASSBURGER, 2017). Lubosch, Kunath e Winkler (2018) proposed an algorithm that combines Monte Carlo Tree Search and Decision Tree to improve the production system's performance. This flexible scheduling algorithm can easily adapt to different types of problems and situations while still finding near-optimal schedules. The results show that a combination of these two techniques is a promising way to handle complex industrial scheduling problems. Finally, Genetic Algorithms (GA) was the fourth most technique applied in the portfolio's papers. The GA could be used as a feature selection method to search for an optimal feature subset from a large number of candidates (SHAPIRO, 2011). Ma, Qiao e Lu (2016) proposed a learning-based scheduling framework for semiconductor manufacturing system. For this, the hybrid algorithm based on GA, Simulated Annealing (SA) and Extreme Learning Machine (ELM) was developed. The result indicates that the proposed method satisfies the requirement of real-time scheduling well and gets better performance compared to using the ELM method only.

In summary, the papers in the portfolio show that the adoption of ML techniques has been attracted much attention in recent years. Especially in production scheduling since it's one of the most important activities in a manufacturing company. Figure 10 shows the evolution of the four main ML techniques mentioned in the portfolio and described previously. This graphic gives an overview of the evolution of these methods for this specific, small selection of papers.

Figura 10 – Temporal evolution of the main ML techniques



Fonte: Elaborada pelos autores (2020).

Among the four techniques, it is possible to notice that there was a growth mainly in the use of the technique of ANNs. Such fact may be justified due to currently a huge quantity of data available to train neural networks, and ANNs frequently outperform other ML techniques on very large and complex problems (GÉRON, 2019). In addition, there was also an increase in the use of Regression methods. Regression is a useful and widely used statistical learning method since many fancy statistical learning approaches can be seen as generalizations or extensions of Regression methods (JAMES *et al*., 2013).

In the end, there are a wide variety of aspects that need to be considered when developing production scheduling models. Due to the nature of the manufacturing systems, there is no best technique for all scenarios, settings, and objective functions. However, manufacturing processes have been updated to follow the trends pointed out by Industry 4.0 and, more studies applying ML techniques can increase knowledge in this field of research.

3.2.5 Conclusion and further research

This research paper conducted a systematic literature review to explore the use of machine learning in production scheduling in the Industry 4.0 context. This research realized a bibliometric analysis and identified the main machine learning techniques currently employed to improve production scheduling.

The analysis of 31 papers shows that the number of publications has grown constantly since 2015, this shows a great interest in the application of machine learning techniques in the production scheduling environment. Additionally, emerging themes have been identified. Terms like "*machine learning techniques*" and "*learning system*" are considered a recent field to deserve more studies and exploration, especially for manufacturing systems environments. In summary, many different approaches to im-prove scheduling in dynamic stochastic environments have been studied. However, it is important to develop more studies applying these techniques to provide more results and knowledge about this emerging field in the Industry 4.0 context.

For the bibliometric analysis only 31 papers have been used which have been published from 2011 on. For further research it might be interesting to also consider older paper and approaches. This would also lead to more significant results regarding the total usages of the different methods. But this paper focusses on the research since the establishment of the term Industry 4.0 and therefore gives a good overview of the main machine learning techniques applied in production scheduling. So, it answers the paper's research question and therefore the study's purpose was achieved. For future research, manufacturing is an area where the application of machine learning can be very fruitful. The inclusion of these techniques for predictive and reactive production scheduling could be a good way to face the disruptions during the production execution. Moreover, the exploration of other machine learning techniques that have not been studied extensively in the analyzed portfolio's papers is an interesting field, capable of providing more insight into the behavior and the possible advantages of such techniques by applying them at production scheduling problems.

Acknowledgements

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3.3 PREDICTIVE-REACTIVE PRODUCTION SCHEDULING REVIEW: A CONCEPTUAL MODEL INTEGRATING INVENTORY AVAILABILITY

Esta subseção apresenta o Artigo[3] 1.3, o qual foi submetido à publicação.

Abstract: Production scheduling in a dynamic manufacturing system embodies a very challenging task. The production resources schedules often need to be adjusted due to unexpected events, which can hinder production performance. Therefore, the adoption of strategies such as predictive-reactive production scheduling aims to ensure the stability of production processes. In this context, this paper aims to propose a conceptual model for a predictive-reactive production scheduling approach, which considers inventory availability. A conceptual model was proposed accordingly to the highlights and gaps found in a systematic literature review (SLR). The SLR showed that few studies addressed the integration of inventory with production scheduling in the operational and short-term horizon. The contribution of this paper is two-fold. For the scientific community, the proposed model presents a method not previously adopted, integrating inventory information into production scheduling in the short-term. Moreover, it provides a forward-looking research agenda. For the praxis-oriented community, the method allows for decision-making in reactive scheduling situations. It targets the stability of production execution, avoiding system disruption and ensuring production performance.
Keywords: Production Scheduling; Inventory; Predictive-reactive; Industry 4.0; Literature Review.

3.3.1 Introduction

Traditionally, manufacturing systems are responsible for managing the production scheduling and execution with the capability of maintaining the production operations regardless of a given perturbation. The manufacturing environment is complex and challenging, requiring the system to react and adapt to achieve optimal performance after a perturbation occurs (ALKAN *et al.*, 2018; JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018). With the advent of the fourth industrial revolution, also known as Industry 4.0, manufacturing systems are advancing to an intelligent level. That is, intelligent manufacturing takes advantage of advanced information and manufacturing technologies to achieve flexible, smart, and reconfigurable manufacturing processes that increase the complexity of manufacturing (CHEN, 2017; CORDEIRO; ORDÓÑEZ; FERRO, 2019).

In this sense, several research projects were developed that address the production scheduling, since it is an important decision-making process in the process industries (ARAMON BAJESTANI; BANJEVIC; BECK, 2014; CAMPOS *et al.*, 2020; DELGOSHAEI;

[3] TAKEDA-BERGER, S. L.; FRAZZON, E. M.; YOKOYAMA, T. T.; OLIVEIRA, M. A. d. Predictive-reactive production scheduling review: a conceptual model integrating inventory availability. Submitted, 2022.

MIRZAZADEH; ALI, 2018; FRAZZON *et al.*, 2015; FRAZZON; KÜCK; FREITAG, 2018; PINEDO, 2018). Besides that, the real-time schedule execution tracking is important to guarantee the allocation of resources to tasks over time and the delivery commitment (UHLMANN *et al.*, 2018). A great effort has been spent on the research of scheduling strategies (HARJUNKOSKI *et al.*, 2014; LIU *et al.*, 2019; UHLMANN; FRAZZON, 2018; VIEIRA; HERRMANN; LIN, 2003). In the literature, one of the strategies studied is predictive-reactive scheduling. Predictive-reactive scheduling is a common strategy for rescheduling dynamic manufacturing systems, which has two steps. The first one establishes a production schedule using a predictive mechanism, and the second one updates the schedule in response to disruptions to minimize their impacts on the scheduling system (TANG; WANG, 2008).

The most common approaches found in the literature about predictive-reactive production scheduling are related to interruptions caused by machine breakdowns, changes in machine operation, and modification or cancellation of orders (LI; IERAPETRITOU, 2008). However, there is a research gap related to a production scheduling approach that reacts based on inventory availability data, i.e., provides a new schedule due to an event caused by non-availability of material. Inventory has an essential function in scheduling and can impact the overall manufacturing costs. Hence, aiming to bridge this gap, three research questions guided this paper:

> RQ1. *Which are the studies that have adopted the strategy of predictive-reactive production scheduling?*
> RQ2. *Which are the studies that dealt with production scheduling based on inventory?*
> RQ3. *How have the production scheduling strategies been applied?*

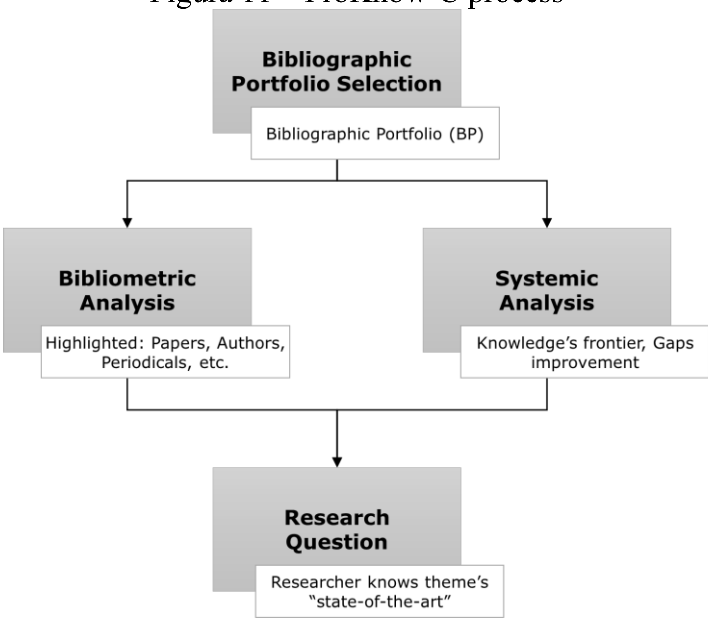
To answer these research questions, this paper conducted a systematic literature review (SLR) and, afterwards, proposed a conceptual model. The SLR provided an insight about the theme in the scientific field and over time. Additionally, it explored previous studies that addressed the integration between inventory and production scheduling and identified the main methods applied for production scheduling. The technique ProKnow-C (*Knowledge Development Process – Constructivist*) was chosen to conduct the SLR since it presents a structured process of literature analysis and the construction of scientific knowledge based on a relevant bibliographic portfolio (DUTRA *et al.*, 2015; ENSSLIN *et al.*, 2015). Several authors have used a SLR to propose a conceptual model that integrates the most important concepts in a different field (HECKMANN; COMES; NICKEL, 2015; IGARASHI; DE BOER; FET, 2013; RAMASESH; BROWNING, 2014).

The contribution of this paper is threefold. First, there has been no previous SLR seeking to analyse the integration of inventory control with production planning and control. Second, a conceptual model is developed as a result of this SLR, that provides an insight into how owners and managers can integrate inventory availability in production scheduling and react in real-time. Finally, it provides the academic field with an agenda for future research.

3.3.2 Research method

The systematic literature review (SLR) was conducted using ProKnow-C structured process. The ProKnow-C is composed of four macro stages: (*i*) selection of a portfolio of papers about the research topic; (*ii*) bibliometric analysis; (*iii*) systemic analysis; and (*iv*) definition of the research question (ENSSLIN *et al.*, 2015). In stage (*iii*), the researcher is led to reflect on the content of the papers selected in stage (*i*). Figure 11 shows the macro stages of the ProKnow-C technique.

Figura 11 – ProKnow-C process



Fonte: Adaptado de Ensslin *et al.* (2015).

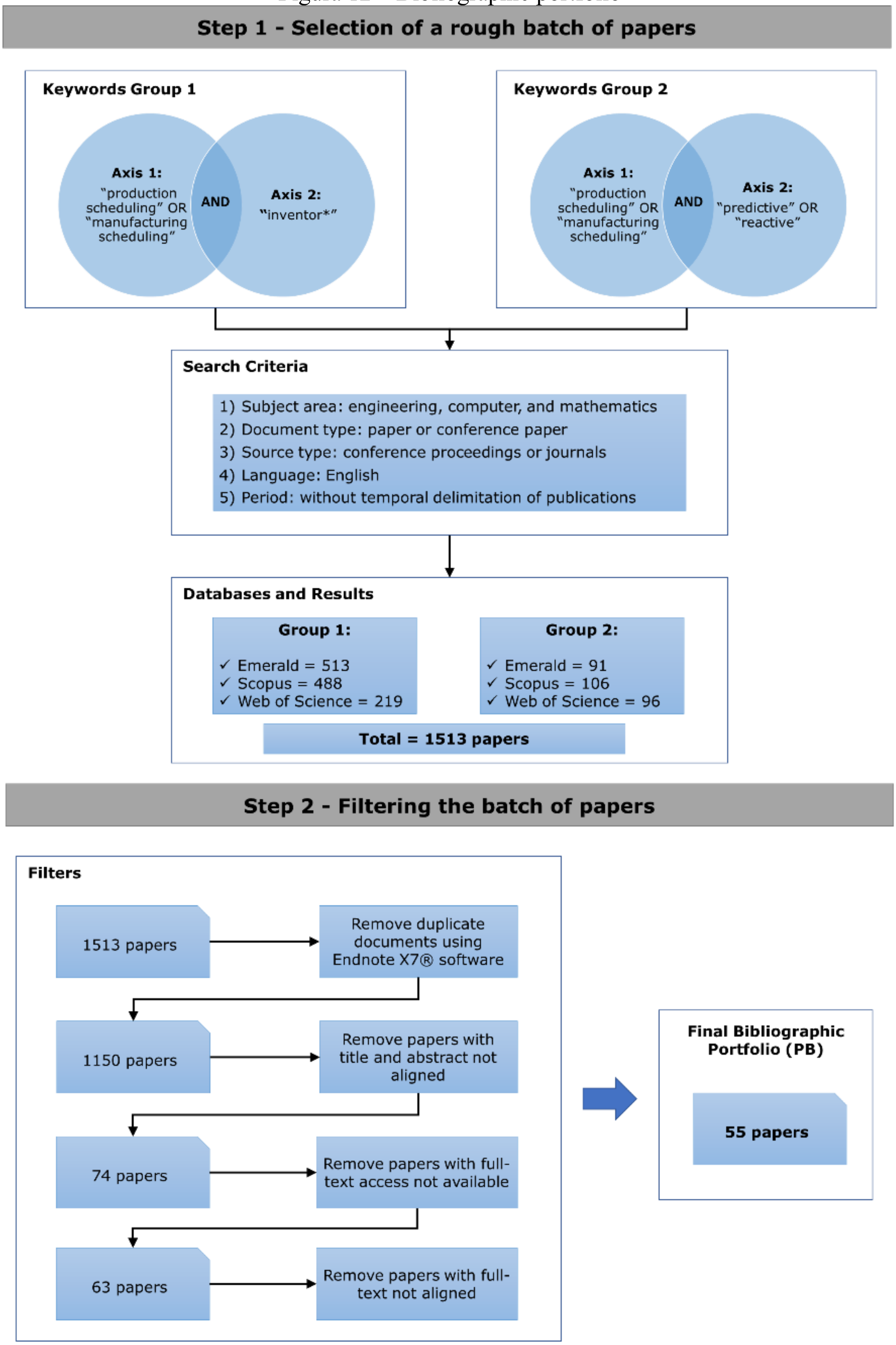
3.3.2.1 Stage 1: Bibliographic portfolio

The first stage of the ProKnow-C technique is to generate the bibliographic portfolio (BP), following two steps: (*i*) selection of a rough batch of papers; and, (*ii*) filtering of this batch of papers. Figure 12 shows these two steps.

In the first step (*i*), the keywords and the databases are defined, and the papers are searched for. The keywords contained in the axes groups were used to search for papers in the chosen databases: Emerald, Scopus, and Web of Science (formerly ISI Web of Knowledge). According to the criteria established for criteria (1) the areas were extended to computing and mathematics, since both areas also develop studies on operations research, to which the theme of this paper belongs. Also, for criteria (2) and (3) was opted to include papers beyond journals, in order to cover more studies and trends published in conference as well. Moreover, in criteria (5) the initial period of the search was not limited, as to obtain an evolution of the theme until the period in which the search was conducted in February 2019.

In conclusion to step (*i*), a keywords adherence test was conducted to validate the keywords used in the initial search. For this, five papers were randomly selected from the 1513 publications and their keywords were compared to the research axes groups (ENSSLIN *et al.*, 2015). Therefore, it was possible to confirm that the keywords used in the search were present in the papers' keywords, meaning it was not necessary to change the axes groups' keywords.

Figura 12 – Bibliographic portfolio



Fonte: Elaborada pelos autores (2022).

The second step (*ii*) aims to form the bibliographic portfolio, and for this, five actions are taken: removal of duplicate papers, alignment by pertinent abstract, alignment by scientific relevance, gaining full access to the paper, and, finally, alignment by reading the full papers (TASCA *et al.*, 2010). As a result, the BP is composed of the most relevant papers for the knowledge area, which were aligned according to the perception and the boundaries established by the authors of this research (ENSSLIN *et al.*, 2015).

3.3.3 Result and discussion

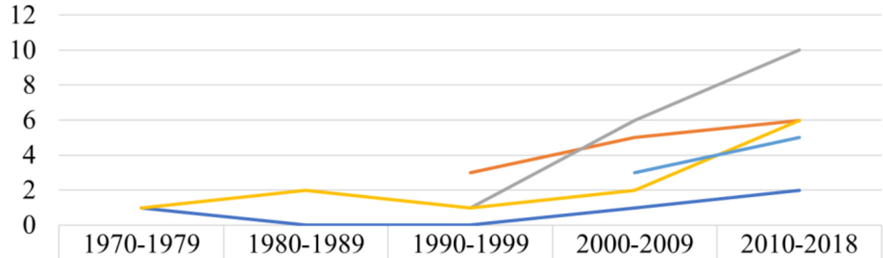
3.3.3.1 Stage 2: Bibliometric analysis

The bibliometric analysis was conducted using the Bibliometrix tool. This tool was developed in R (R CORE TEAM, 2019), an open-source language that provides a wide variety of statistical and graphical techniques enabling a comprehensive scientific mapping (ARIA; CUCCURULLO, 2017). For the bibliometric analysis, the BP with 55 papers was considered and evaluated according to the following different dimensions: papers per year, papers per journal, and most relevant authors and cited papers.

3.3.3.1.1 Publication year of the papers

Figure 13 shows the publication year of the BP's papers. This filter is useful for comparing papers in different time slices indicating the historical evolution. According to the defined keywords, the selected papers presented different production scheduling strategies. Thus, to better represent the evolution of the theme over the years, the papers were categorized according to the strategy adopted, which were: 'predictive', 'reactive' or 'predictive-reactive'. For papers that did not adopt a defined strategy, they were categorized as 'production scheduling', and another defined category was for review papers.

Figura 13 – Evolution of the publications



	1970-1979	1980-1989	1990-1999	2000-2009	2010-2018
Predictive	1	0	0	1	2
Reactive			3	5	6
Predictive-reactive			1	6	10
Production scheduling	1	2	1	2	6
Review				3	5

Fonte: Elaborada pelos autores (2022).

The first paper was published in 1975, focusing on predictive production scheduling, addressing in its model machine breakdowns, material availability, and demand variation. In 1978, another paper was published on production scheduling. The paper did not address a specific production scheduling strategy, but in its proposal, it considered inventory and distribution to schedule production.

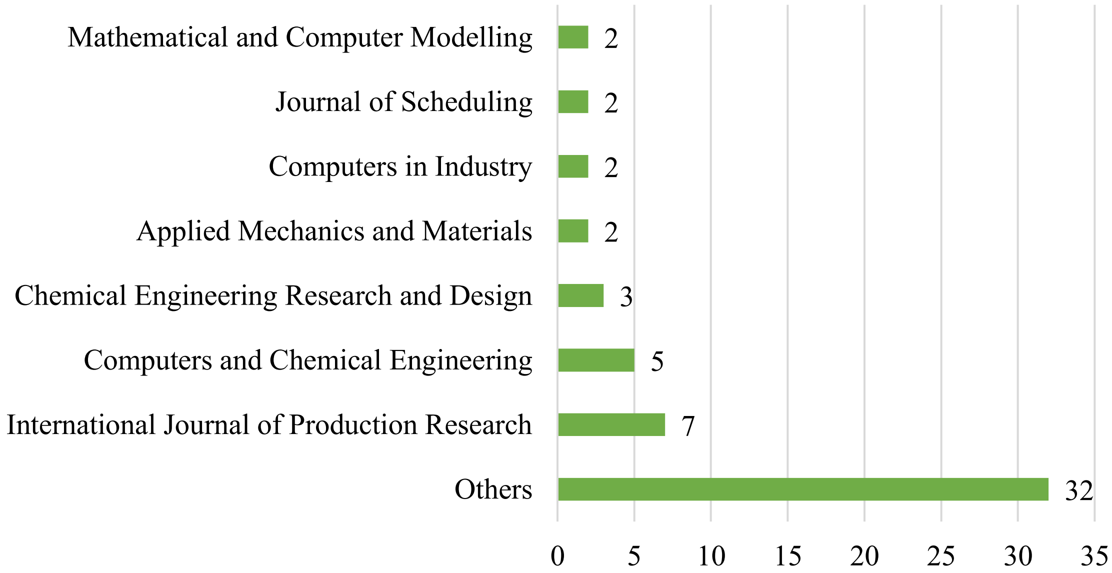
Publications discussing the reactive and predictive-reactive strategies for production scheduling appear from the 1990s on. From the new millennium, the publications that focused on the predictive-reactive scheduling strategy had a significant increase. Until the date of this research, 5 papers had been published in 2018, among them 3 addressed the predictive-reactive strategy and 2 papers did not cover any strategy.

Furthermore, from 2003 onwards literature review papers started to be published. This is expected, because only after a few years of the emergence of a theme becomes relevant to perform a literature review to understand what has already been researched and future directions. However, the last review papers were published in 2016 and no review has so far focused on investigating the integration of inventory in the predictive-reactive production scheduling strategy.

3.3.3.1.2 Quantity of papers per journal

Figure 14 shows the most relevant journals in BP. From the set of the 55 papers, 37 are from journals, and 18 are from conference proceedings. The category classified as "others" contains 32 papers from different journals or conference proceedings, representing 58%. The International Journal of Production Research contains the most significant number of published papers, followed by Computers and Chemical Engineering and Chemical Engineering Research and Design.

Figura 14 – Quantity of papers per journal

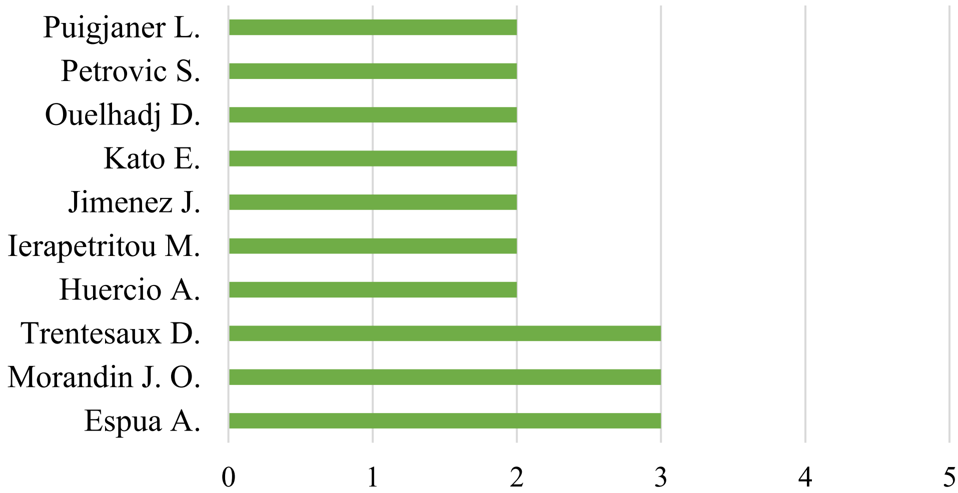


Fonte: Elaborada pelos autores (2022).

3.3.3.1.3 Most relevant authors and cited papers

The BP's analysis allowed for the identification of 138 authors with an average of 2.51 authors per paper, this average being considered typical of international journals (DUTRA *et al.*, 2015). Figure 15 shows the most relevant authors, i.e., those who authored more than one of the papers in the BP. The remaining authors have only one paper and are not presented in Figure 6. The authors Espua A., Morandin J. O., and Trentesaux D. have three papers in the BP, and the remaining seven authors have two papers each.

Figura 15 – Quantity of papers per most relevant authors



Fonte: Elaborada pelos autores (2022).

Chart 3 shows the Top 5 most cited papers in BP. The papers were analysed according to the number of citations in Google Scholar, thus making the highlighted papers evident. The paper by Vieira, Herrmann e Lin (2003) is a highlighted paper with a higher number of citations in Google Scholar. This paper introduced definitions for most rescheduling applications in manufacturing systems, and also presented a framework for rescheduling strategies, policies, and methods. Thus, the significant number of citations of this paper could be explained by the provision of a theoretical basis for further research.

Quadro 3 – Most cited papers

Paper	Authors	Year	Source	Citations
Rescheduling manufacturing systems: a framework of strategies, policies, and methods	Vieira, G. E., Herrmann, J. W. and Lin, E.	2003	Journal of Scheduling	804
A survey of dynamic scheduling in manufacturing systems	Ouelhadj, D. and Petrovic, S.	2008	Journal of Scheduling	594
Process scheduling under uncertainty: Review and challenges	Li, Z. and Ierapetritou, M.	2008	Computers & Chemical Engineering	303
Production scheduling/rescheduling in flexible manufacturing	Jain, A. K. and Elmaraghy, H. A.	1997	International Journal of Production Research	206
A scheduling rule for job release in semiconductor fabrication	Glassey, C. R. and Resende, M. G.	1988	Operations Research Letters	138

Fonte: Elaborado pelos autores (2022).

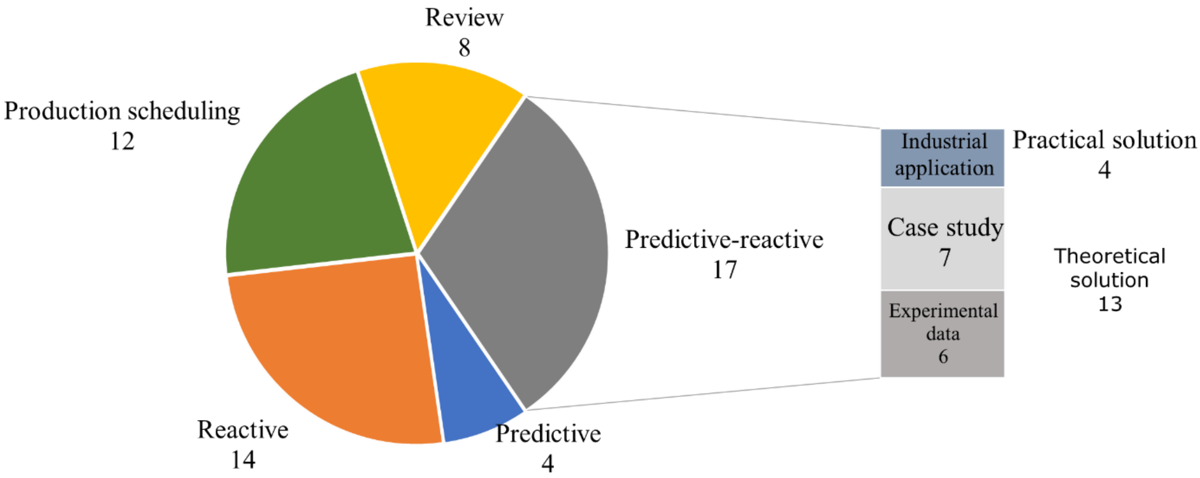
3.3.3.2 Stage 3: Systemic analysis

In this third stage, the BP's papers are analysed in order to answer the three research questions.

3.3.3.2.1 Which are the studies that have adopted the strategy of predictive-reactive production scheduling?

Figure 16 illustrates the classification of the papers in relation to the content-based category. Among the 55 papers, 17 adopted the predictive-reactive production scheduling strategy. The remaining papers in the BP were divided between those that adopted the strategies in isolation, i.e., predictive or reactive, those that did not adopt any strategy and were only studies on production scheduling or review papers.

Figura 16 – Papers classified by content-based category



Fonte: Elaborada pelos autores (2022).

Literature review papers are important when analysing what has already been explored in an area of interest, providing a theoretical background. The papers of Ouelhadj e Petrovic (2009) and Chaari *et al.* (2014) reviewed production scheduling approaching predictive-reactive scheduling. For the authors, the predictive-reactive strategy comprises two phases. In the first one, an offline deterministic schedule is established, i.e., the events (e.g., available resources, deterministic process times) are considered predictable. During the second phase, this schedule is used and adapted online. Vieira, Herrmann e Lin (2003) presented definitions appropriate for most applications of rescheduling manufacturing systems and described a framework for understanding rescheduling strategies, policies, and methods. Li e Ierapetritou

(2008) reviewed the main methodologies that have been developed to address the problem of uncertainty in production scheduling as well as to identify the main challenges in this area.

Baldea e Harjunkoski (2014) analysed the advances in integrating production scheduling and process control. These fields have evolved quite independently of each other, but they have the common aim of identifying optimal operational decisions. Díaz-Madroñero, Mula e Peidro (2014) investigated the literature on optimization models for tactical production-planning problems. Dias e Ierapetritou (2016) reviewed some of the efforts to optimize performance in the control and scheduling areas and their integration under process uncertainties. Finally, the paper by Gupta, Maravelias e Wassick (2016) reviewed the advances in rescheduling. The authors commented that traditional event-triggered rescheduling has some shortcomings that can be addressed if rescheduling is approached as an online problem.

As shown in Figure 16, four papers conducted practical implementation in an industrial environment. Lee, Kang e Park (1996) developed a Collaborative Scheduling System (CSS) for the job shop to manage the job processing effectively, adopting a predictive-reactive scheduling strategy. As a result, the company achieved a reduction in manufacturing lead time of 25% on average and an improvement of machine utilization of 10 to 20%. The authors Pach *et al.* (2014) and Jimenez *et al.* (2016) implemented their research in a real flexible job shop manufacturing system, located at the Université de Valenciennes et Hainaut-Cambrésis, called AIP PRIMECA. Pach *et al.* (2014) developed a new generic hybrid control architecture called ORCA (dynamic Architecture for an Optimized and Reactive Control). This hybrid architecture can dynamically and partially switch between a hierarchical predictive architecture and a heterarchical reactive architecture if an event forbidding the planned behaviour to be followed occurs. This paper only considered the behaviour of the ORCA in the event of a machine breakdown. Jimenez *et al.* (2016) presented a switching mechanism framework in dynamic hybrid control architectures, to explore the advantages of hierarchical manufacturing scheduling systems and heterarchical manufacturing execution systems. The hybrid control architectures aimed to achieve optimal production scheduling (predictive scheduling) and to react to unexpected events (reactive control). The paper by Garcia *et al.* (2008) will be discussed in the next subsection.

The papers by authors Cowling, Ouelhadj e Petrovic (2004), Petrovic e Duenas (2006) and Garcia et al. (2008) will be discussed in the next subsection. Thus, to facilitate analysis of the 11 remaining papers, Chart 4 compiles these papers and classifies them into five categories: (1) Authors; (2) Type; (3) Industry segment; (4) Approach and (5) Outlines. In category (2), the paper was classified as case study or experimental data, i.e., whether the paper used real data to test the approach or only theoretical data, respectively. If a case study has been conducted, category (3) identifies in which industry segment the study was carried out. Regarding category (4), the approaches considered in the studies are indicated. Here, it is identified whether previous studies have approached the inventory availability to integrate the production scheduling. Finally, category (5) provides the summary of the papers in outlines.

Even though the theme related to production scheduling is widely brought up in the literature, few studies have focused on the adoption of the predictive-reactive strategy, only 31% of the BP. In particular, little attention has been given to the integration of inventory into production scheduling, with only three papers addressing the predictive-reactive strategy based on inventory (COWLING; OUELHADJ; PETROVIC, 2004; GARCIA *et al.*, 2008; PETROVIC; DUENAS, 2006). The next subtopic will discuss this research gap.

Quadro 4 – Papers that have adopted the strategy of predictive-reactive production scheduling

(continua)

Authors	Type	Industry segment	Approach	Outlines
Sun e Xue (2001)	Case study	Building Products Industry	- Order cancellation - Rush order arrival - Machine breakdown - Manpower availability	Development of a reactive scheduling method for an intelligent production scheduling system. This method considers a previously predictive scheduling for identifying the optimal production schedule based on manufacturing requirements and resource constraints.
Hauptman e Jovan (2004)	Case study	Chemical Industry	- Quality of raw materials - Production process variation - Machine breakdown - Power supply interruptions	Proposition of a batch-launching algorithm to develop predictive-reactive scheduling in order to continuously update the predictions based on the current process status. This approach assigns a new batch at the earliest possible starting time, respecting all predefined constraints.
Tang e Wang (2008)	Case study	Steel Industry (Baosteel, China)	- Machine breakdown - Production process variation - Transport capacity	Proposition of a predictive-reactive scheduling method to reduce the impact on the previously established schedule and maintain production execution. The results showed that the proposed method provided a scheduling for real-time production.
Abu, Yamada e Terano (2010)	Case study	Steel Industry	- Production process failures	Proposition of a predictive-reactive scheduling approach to minimize production delay and constraints control. The approach considered three performance measures as utility, stability, and robustness, to assess the value and impact of the rescheduling strategy in response to real-time events.
Kalinowski, Krenczyk e Grabowik (2013)	Experimental data	Not Applicable (NA)	- Machine breakdown - New order arrival - Order cancellation	Proposition of a real-time scheduling in manufacturing systems using a predictive-reactive strategy and multi-thread searching approach with rule-based heuristics, meta-heuristics, and random modules. The method can act in a variable environment or provide solutions for a limited and guaranteed time.

Fonte: Elaborado pelos autores (2022).

Quadro 4 – Papers that have adopted the strategy of predictive-reactive production scheduling

(conclusão)

Authors	**Type**	**Industry segment**	**Approach**	**Outlines**
Akkan (2015)	Experimental data	NA	- New order arrival	Proposition of a predictive-reactive scheduling strategy in the scheduling planning phase. The approach considers the arrival of a new order as a disruption, and generates a new schedule in order to obtain the minimal maximum tardiness.
Barták e Vlk (2015)	Experimental data	NA	- Machine breakdown	Proposition of a technique to recover a schedule due to machine breakdown. The approach seeks to find a viable schedule, similar to the original, as fast as possible. Two methods were proposed: right-shift of affected activities and simple temporal network recovery.
Bozek e Wysocki (2016)	Case study	Fastener Industry	- Lot streaming - Machine availability - Transport times - Setup times	Presentation of three different methods for production scheduling. The aim is to provide suggestions on methods and implementation of algorithms for production scheduling. The proposed solutions were verified in the problem of flexible job shop.
Sobaszek, Gola e Świć (2018)	Experimental data	NA	- Machine breakdown - Processing time variation	Presentation of a predictive-reactive scheduling system for job shop under uncertainty. The approach performs the production scheduling using machine learning features. Thus, the proposed system allows the scheduling optimization avoiding errors that generate divergence between the scheduled model and the real production process.
Jimenez, Gonzalez-Neira e Zambrano-Rey (2018)	Experimental data	NA	- New order arrival	Proposition of a predictive-reactive control strategy for a dynamic scheduling problem. The approach aims to reduce job delays, thus combines two algorithms, one for predictive scheduling and other for reactive scheduling.
Valledor *et al.* (2018)	Experimental data	NA	- New order arrival - Machine breakdown - Processing time variation	Proposition of a predictive-reactive scheduling method to calculate the reactive scheduling in each rescheduling period. Additionally, the authors developed a methodology that allows the use of multi-objective performance metrics to evaluate the dispatching rules.

Fonte: Elaborado pelos autores (2022).

3.3.3.2.2 Which are the studies that dealt with production scheduling based on inventory?

Among the 47 papers that addressed production scheduling (excluding the 8 review papers), only 12 papers addressed production scheduling based on inventory. Chart 5 presents the summary of the analyzed papers. To classify the papers, it was used the same categories presented in the previous subsection, in Chart 4. However, a category was added in order to classify the strategy adopted, as follows: P (predictive scheduling), R (reactive scheduling), PR (predictive-reactive scheduling), and PS (production scheduling) for the papers that did not adopt any of the strategies.

Quadro 5 – Papers that dealt with production scheduling based on inventory

(continua)

Authors	Type	Industry segment	Scheduling strategy	Approach	Outlines
Smith e Crabtree (1975)	Experimental data	Not Applicable (NA)	P	- Machine breakdown - Material availability - Demand variation	Predictive information was developed as a logical extension of the simulation model structure, to help answer problems and enable decision-making within the experimental context of a job shop industrial problem-production scheduling.
Overturf, Reklaitis e Woods (1978)	Case study	Film Extrusion Industry	PS	- Production orders allocation - Material availability - Stock replenishment order	The simulation model developed included inventory and distribution and used some techniques to programming the production scheduling in order to debottlenecking studies, to evaluate plant operating policies, and to perform parameter sensitivity studies.
Glassey e Resende (1988)	Experimental data	NA	PS	- Machine breakdown - Machine repair - Inventory control	A method for stochastic job shop considering machine failure and repair was developed. The aim is to find a strategy that adapts concepts of inventory control to the context of job shop scheduling.
Ahmadi e Iqbal Ali (1988)	Experimental data	NA	PS	- Limited production and manpower - Delays (high setup) - Processing time variation - Machine breakdown - Inventory cost	Presentation of a method that integrates planning, scheduling, and production management. The method considers work-in-process, optimization of the performance of the various subsystems, minimization of setup time effect, and inventory carrying costs. The experimental test used data from new electronic card assembly lines.
Cheng (1990)	Experimental data	NA	PS	- WIP inventory - Order delivery	Formulation of a dynamic programming that aim to find an optimal order to process the jobs that minimizes a penalty function. Minimizing this function, the WIP inventory is reduced, and also the missed due-dates are minimized to improve order delivery performance, directly affecting customer satisfaction.
Huercio, Espuña e Puigjaner (1995)	Case study	Chemical Process Industry	R	- Availability of: material, equipment and manpower - Utility consumption	Presentation of a reactive scheduling algorithm that adapts the current schedule to real-time disturbances. The disturbances are integrated into a system that deals with the new schedule generated, rescheduling high production scheduling and low levels of sequential control.

Fonte: Elaborado pelos autores (2022).

Quadro 5 – Papers that dealt with production scheduling based on inventory

(conclusão)

Authors	Type	Industry segment	Scheduling strategy	Approach	Outlines
Luh, Zhou e Tomastik (2000)	Case study	Sikorsky Aircraft	PS	- CONWIP - Machine capacity	Presentation of a new method addressing the concept of constant work-in-process (CONWIP). This method can control the WIP inventory in a job shop environment and maintain a good delivery performance.
Cowling, Ouelhadj e Petrovic (2004)	Case study	Steel Industry	PR	- Rush order arrival - Material availability	Presentation of a multi-agent approach for dynamic scheduling. Each agent has the autonomy to execute the local predictive-reactive scheduling considering real-time information and also received from other agents. Agents collaborate to find a favorable schedule that can react to real-time disruptions effectively.
Petrovic e Duenas (2006)	Case study	Pottery Company	PR	- Material availability: number of shortage occurrences and shortage duration (raw material shortage)	Presentation of a new predictive-reactive scheduling approach that considers material shortage defined by the number of occurrences and the duration of the material shortage. Two sets of rules are used to perform rescheduling, one to define when rescheduling should occur and the other to choose which rescheduling method should be used.
Garcia *et al.* (2008)	Case study (Practical)	Ceramic Tile Industry	PR	- Material availability - Processing time variation - Addition or modification of orders - Machine breakdown	Presentation of a Flexible and Adaptive Scheduling Tool (FAST) to develop a flexible, fault-tolerant, and scalable scheduling system. The test results demonstrated that the prototype is reliable, flexible, and efficient under normal conditions as well as under nonstandard operating circumstances.
Luo *et al.* (2012)	Case study	Aluminium Industry	PS	- Multiple processing routes - Inventory capacity	Presentation of an approach to production scheduling in a manufacturing system where one item is transformed into multiple items. This approach considered two problems, first a product can be produced following different process routes with different capability and capacities, and second the inventory capacity is limited.
Li e Zhang (2018)	Experimental data	NA	PS	- Processing time variation - Machine breakdown - WIP inventory	Development of a model for balancing between utilization and work-in-process inventories. The approach aims to present a consistent performance for adaptive production scheduling and control with variation in processing times.

Fonte: Elaborado pelos autores (2022).

From the 12 papers, 11 proposed theoretical solution (i.e., case study with real data or experimental data) and only 1 paper proposed practical solution. In addition, most papers (7 papers) did not address any specific strategy for the production scheduling based on inventory, with only 1 paper addressing the predictive strategy, 1 the reactive strategy, and 3 the predictive-reactive strategy.

From Chart 5, it can be concluded that few papers considered the integration of inventory control and production planning and control. In general, papers were included that somehow covered inventory in their proposals, either through material availability, inventory control, inventory cost, work-in-process (WIP), or inventory capacity. However, most of the papers (8 papers) did not adopt a strategy to react to non-availability of material, considering only the inventory as an initial condition for scheduling planning. In addition, only 3 papers approached the strategy of predictive-reactive production scheduling based on inventory, but none of them presented a proposition of new methods facing the current context of manufacturing systems, since the most recent paper was published thirteen years ago. Thus, with the advent of Industry 4.0, research opportunities arise to explore new approaches for production scheduling that are more efficient and adaptive to change (ZAMORA *et al.*, 2017).

The remaining 21 papers were compiled in Chart 6. The classification used the same categories as in the previous table (see Chart 5). Among these papers, 13 addressed the reactive strategy, 3 the predictive strategy, and the rest, 5 papers, did not address any of the strategies mentioned. Notably, machine breakdown is the approach that most appears in the research, which characterizes being the disruption most considered in production scheduling planning.

Quadro 6 – Summary of the remaining papers

(continua)

Authors	Type	Industry segment	Scheduling strategy	Approach	Outlines
Sanmartí *et al.* (1996)	Case study	Pigment Industry	R	- Processing time variation - Equipment availability	Proposition of a method with reactive scheduling to adapt the original schedule to the new scenario. This method aims to improve system efficiency by considering variations in task processing times and equipment availability.
Jain e Elmaraghy (1997)	Experimental data	Not Applicable (NA)	R	- Machine breakdown - Rush order arrival - Increased order priority - Order cancellation	Presentation of a new scheduling approach based on genetic algorithms and reactive scheduling or rescheduling algorithms. This approach can be used to complement the existing scheduling methods to improve the efficiency of flexible manufacturing systems.
Mesghouni e Rabenasolo (2002)	Experimental data	NA	P	- Demand variation	Formulation of the scheduling problem with the uncertain demand model. Two jobs lists were considered, the actual orders and the predicted order to be scheduled at the time. As a result, it is possible to analyse how actual jobs scheduling solutions given by the genetic algorithm are re-evaluated considering future jobs.
Janak *et al.* (2006)	Case study	Industrial Batch Plant	R	- Machine breakdown - Addition or modification of orders	Development of a reactive scheduling framework that used mixed-integer linear programming (MILP) for short-term scheduling problems. The reactive scheduling was developed to react to disruptions such as unit shutdown and order addition or modification.
Al-Aomar (2006)	Case study	Automotive Pilot Plant	PS	- Production capacity	Presentation of a production scheduling approach to solve the problem of limited capacity and increase the efficiency of production scheduling. The approach uses simulation to solve the capacity problem and an algorithm to increase the efficiency of production scheduling.
Sawik (2007)	Case study	Electronics Industry	R	- Addition, modification, or cancellation of orders	Proposition of new algorithms for reactive scheduling in a dynamic manufacturing. The approach allows updating the production schedule considering modifications, cancellations, or new orders arrival. The algorithms are based on mixed integer programming.

Fonte: Elaborado pelos autores (2022).

Quadro 6 – Summary of the remaining papers

(Continuação)

Authors	Type	Industry segment	Scheduling strategy	Approach	Outlines
Sakaguchi *et al.* (2008)	Experimental data	NA	R	- Production process failures	Proposition of a reactive scheduling method for aggregate production schedule. The schedule is divided into three parts: a fixed part that cannot be changed and the other two parts that can be rescheduled, one by genetic algorithm and the other by dispatching rule. The objective of the method is to minimize the number of tardy jobs.
Kato, Morandin Jr e Fonseca (2009)	Experimental data	NA	R	- Production orders allocation	Presentation of a modeling and analysis of a reactive production scheduling problem in a job shop system. The method aims at allocating production operations in order to minimize production time.
Morandin Jr *et al.* (2009)	Experimental data	NA	R	- Shared resources - Transport times	Development of a reactive production scheduling approach based on an algorithm. The approach considered manufacturing systems with shared resources and Automated Guided Vehicles to achieve acceptable response time and production time.
Ben-Awuah *et al.* (2010)	Case study	Iron Ore Mine	PS	- Production capacity - Equipment availability - Manpower availability - Stocking and blending requirements	Development of a discrete event simulation model to connect long-term predictive plans with short-term production schedules amidst uncertainties. The model considered uncertainties such as plant and processing capacity, equipment availability and utilization, worker availability and downtime, and stocking and blending requirements.
Klimek e Lebkowski (2011)	Experimental data	NA	P	- Equipment availability - Machine breakdown	Proposition of new algorithms for the problem of predictive production scheduling, with the Resource-Constrained Project Scheduling Problem (RCPSP). These algorithms were adjusted to provide sequences of activities characterized by completion times for specific tasks according to milestones.

Fonte: Elaborado pelos autores (2022).

Quadro 6 – Summary of the remaining papers

(Continuação)

Authors	Type	Industry segment	Scheduling strategy	Approach	Outlines
Huang e Liao (2012)	Case study	Aluminum Foil Industry	R	- Machine capacity (parallel machines)	Proposition of a multi-agent based approach for rescheduling parallel machines. The approach has three types of agents: job agents, machine agents, and supervisor agents. In case of a system disturbance, the supervisor agent performs the reactive scheduling to update the current production schedule providing an immediate solution.
Paprocka e Skołud (2013)	Experimental data	NA	P	- Machine breakdown	Presentation of a production model with failures considering the successive failure-free times and repair times with normal distributions. From the meantime to the first failure and meantime of repair, a predictive scheduling with new priority rules is generated.
Tuma, Morandin Jr e Caridá (2013)	Experimental data	NA	R	- Transport times - Production orders allocation - Buffers	Proposition of approach with adaptive genetic algorithm and Tabu Search for reactive production scheduling problem. In this approach, a new chromosome structure of a genetic algorithm has been developed in order to find better makespan results.
Cataldo, Perizzato e Scattolini (2015)	Experimental data	NA	PS	- Energy consumption - Production process variation	Development of an optimization algorithm for production scheduling with multiple lines and parallel machines. The model considered buffer management and aims to limit energy consumption and maximize production.
Setiawan *et al.* (2016)	Case study	Aircraft Industry	R	- Machine breakdown - Machine lifetime	Development of a reactive scheduling algorithm that considers equipment breakdown. The method generates an initial schedule, determines the time of failure, the status at the time of failure, and generates a new schedule.

Fonte: Elaborado pelos autores (2022).

Quadro 6 – Summary of the remaining papers

(Conclusão)

Authors	Type	Industry segment	Scheduling strategy	Approach	Outlines
Calahorrano *et al.* (2016)	Case study	Chemical Industry	R	- Rush order arrival - Order cancellations - Logistic problems - Machine breakdown	Presentation of an approach with Meta-Multiparametric techniques in reactive scheduling. The approach aims to control unexpected changes in the emissions of the chemical plant and for this, it considers continuous and discrete uncertain parameters.
Herrera *et al.* (2016)	Experimental data	NA	R	- Demand variation	Proposition of a reactive approach for production scheduling. The approach aims to generate new schedules to maintain the stability of production with a better cost of production.
Guizzi, Vespoli e Santini (2017)	Experimental data	NA	R	- Machine breakdown - Machine repair	Presentation of a new manufacturing scheduling semi-heterarchical framework architecture to resolve the production planning with a mixed proactive and reactive approach to the job-shop scheduling problem.
Kawaguchi e Fukuyama (2017)	Experimental data	NA	PS	- Energy consumption	Presentation of a reactive tabu search for job-shop scheduling problems. The method optimizes production scheduling and operational planning simultaneously, minimizing the makespan and total energy costs.
Ning e You (2018)	Case study	Chemical Industry	PS	- Demand variation	Proposition of a framework based on data for decision-making under uncertainty. This approach enables optimization, computational efficiency, and easy applicability.

Fonte: Elaborado pelos autores (2022).

3.3.3.2.3 How have the production scheduling strategies been applied?

The development of production planning and scheduling algorithms is often a challenging task since scheduling problems usually have greater computational complexity. Thus, to predict uncertain events and to measure their impact on the schedule, different approaches can be evaluated and compared to choose the most suitable, i.e., several paths that can be identified.

For this purpose, the methods identified in the BP (not considering the 8 review papers) were classified, adapting to Brownlee (2011) and shown in Table 1. The papers were also classified according to the adopted scheduling strategy, as in Chart 5.

Table 1 shows that a great deal of effort has been spent on developing methods for solving problems related to production schedules. Traditionally, scheduling approaches usually consider a deterministic environment, where variation and uncertainty are not very present. However, there are several types of uncertainties that can disrupt production schedules, and taking these aspects into account is challenging. In this sense, the industrial requirements evolved from the traditional performance criteria that considered the static optimality or quasi-optimality for criteria aimed at the reactivity and adaptability of the manufacturing system. Thus, the literature about production scheduling has been expanding rapidly with different approaches (CHAARI *et al.*, 2014).

The review papers by Li e Ierapetritou (2008), Ouelhadj e Petrovic (2009), Chaari *et al.* (2014), Díaz-Madroñero, Mula e Peidro (2014) and Gupta, Maravelias e Wassick (2016) have already conducted an important overview about the methods adopted in production scheduling environment. For this reason, it is possible to compare some of these papers with the methods identified in the BP.

In fact, as discussed by Li e Ierapetritou (2008) and Díaz-Madroñero, Mula e Peidro (2014) mathematical programming formulations have been proposed for a wide range of problems address to production scheduling. The typical mathematical programming approaches considered in production scheduling problems are linear programming, integer linear programming and mixed-integer linear programming (MILP), as identified in many papers in the BP (e.g., Herrera *et al.*, 2016; Janak *et al.*, 2006; Luo *et al.*, 2012; Overturf; Reklaitis; Woods, 1978). Ouelhadj e Petrovic (2009) commented that meta-heuristics (e.g., tabu search, simulated annealing, and genetic algorithm) had been successfully used to solve production scheduling problems.

Tabela 1 – Main methods of the papers

Methods		Production Scheduling Strategy				
		P	R	PR	PS	Frequency
Stochastic Algorithms	Tabu Search		31	14, 19, 37		4
	Reactive Tabu Search				41	1
	(Mixed) Integer Programming		15, 18, 39, 40	32, 36	2, 4, 10, 27, 33, 43	12
Evolutionary Algorithms	(Adaptive) Genetic Algorithm	12	9, 21, 23, 31	16, 25, 45		8
	Genetic Programming		7			1
Swarm Algorithms	Particle Swarm Optimization				27	1
	Ant Colony System		22			1
Immune Algorithms	Clonal Selection Algorithm	30				1
Neural Algorithms	Machine Learning Techniques			44	43	2
Advanced Topics	Multi-agent Systems		28	11, 14, 20, 25, 37		6
	Dynamic Programming				5, 10	2
	Discrete Event Simulation (DES)				17, 24	2
Other	Proposition of new algorithms	26	38, 42	8, 13, 44, 47		7
	Metaheuristic non-specified	1	6	14, 29, 34, 35, 47	2, 3, 10, 17, 46	12

References: [1] Smith e Crabtree (1975); [2] Overturf, Reklaitis e Woods (1978); [3] Glassey e Resende (1988); [4] Ahmadi e Iqbal Ali (1988); [5] Cheng (1990); [6] Huercio, Espuña e Puigjaner (1995); [7] Sanmartí *et al.* (1996); [8] Lee, Kang e Park (1996); [9] Jain e Elmaraghy (1997); [10] Luh, Zhou e Tomastik (2000); [11] Sun e Xue (2001); [12] Mesghouni e Rabenasolo (2002); [13] Hauptman e Jovan (2004); [14] Cowling, Ouelhadj e Petrovic (2004); [15] Janak *et al.* (2006); [16] Petrovic e Duenas (2006); [17] Al-Aomar (2006); [18] Sawik (2007); [19] Tang e Wang (2008); [20] Garcia *et al.* (2008); [21] Sakaguchi *et al.* (2008); [22] Kato, Morandin Jr e Fonseca (2009); [23] Morandin Jr *et al.* (2009); [24] Ben-Awuah *et al.* (2010); [25] Abu, Yamada e Terano (2010); [26] Klimek e Lebkowski (2011); [27] Luo *et al.* (2012); [28] Huang e Liao (2012); [29] Kalinowski *et al.* (2013); [30] Paprocka e Skołud (2013); [31] Tuma, Morandin Jr e Caridá (2013); [32] Pach *et al.* (2014); [33] Cataldo, Perizzato e Scattolini (2015); [34] Akkan (2015); [35] Barták e Vlk (2015); [36] Jimenez *et al.* (2016); [37] Bozek e Wysocki (2016); [38] Setiawan *et al.* (2016); [39] Calahorrano *et al.* (2016); [40] Herrera *et al.* (2016); [41] Kawaguchi e Fukuyama (2017); [42] Guizzi *et al.* (2017); [43] Ning e You (2018); [44] Sobaszek, Gola e Świć (2018); [45] Jimenez, Gonzalez-Neira e Zambrano-Rey (2018); [46] Li e Zhang (2018); [47] Valledor *et al.* (2018).

Fonte: Elaborada pelos autores (2022).

Additionally, Díaz-Madroñero, Mula e Peidro (2014) commented that when the mathematical modelling of production systems is confronted with a complex task, the simulation models could provide a good alternative. Ben-Awuah *et al.* (2010) developed a simulation model to connect long-term predictive mine plans with short-term production schedules in the presence of uncertainty. This model allows to capturing both the positive or negative swings in the operations for all possible values of the uncertain variables.

An important contribution of this section is the identification of papers that began to approach machine learning techniques. This recent occurrence is related to the beginning of the fourth industrial revolution that promotes the development of modern manufacturing systems using techniques to transform the available big data into competitive information for companies. Ning e You (2018) proposed a novel data-driven robust optimization framework for decision-making under uncertainty. In this framework, the authors used the principal component analysis (PCA), a machine learning technique, and also kernel smoothing methods. The authors commented that with the increasing access to uncertainty data and recent advances in machine learning techniques, data-driven optimization paves a new way to decision-making under uncertainty.

In summary, it is possible to conclude that different methods can provide useful information for analysts and managers that deal with production scheduling in manufacturing systems. However, with the advent of Industry 4.0 and vast data availability, there are opportunities for the development of new approaches in production scheduling field.

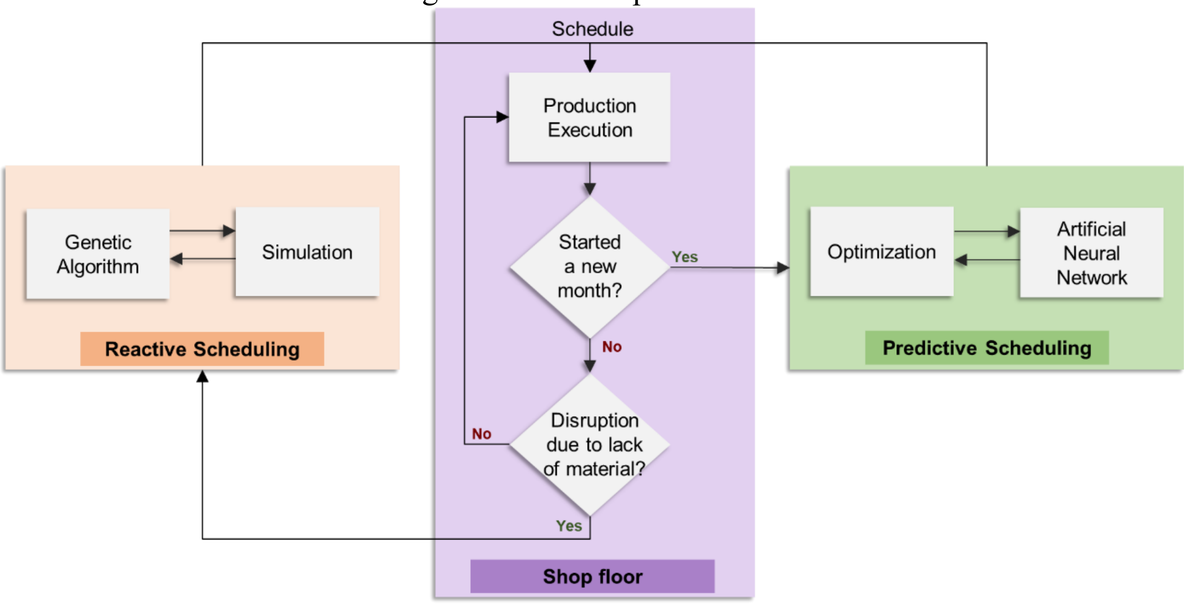
3.3.3.3 Stage 4: Proposed conceptual model as a result of the research question

The previous subsections focused on answering the three research questions that guided the development of this study. However, the last stage of the ProKnow-C technique is the elaboration of a research question related to opportunity that can still be explored. Thus, through the SLR, it was possible to conclude that there are still few studies that have explored the adoption of the predictive-reactive strategy and even more, few studies have dealt with the integration of inventory availability in production scheduling. In fact, it is scarcely explored the integration of inventory for a short-term, i.e., production scheduling reacting and adapting in real-time to changes in inventory availability. Accordingly, considering the results of the SLR and the current scenario of Industry 4.0, bringing new ways of employing technology in manufacturing systems, the research question that arises is:

> RQ. *What approach in the context of Industry 4.0 could be used for predictive-reactive production scheduling based on inventory availability data from the shop floor?*

To answer this question, a conceptual model (CM) is proposed in Figure 17. The CM proposed here is based on the model by Berger, Zanella e Frazzon (2019), which combines two approaches to be integrated on the shop floor, improving production performance. Looking to explore new approaches for production scheduling within the context of Industry 4.0, the CM suggests the use of two approaches: simulation-based optimization (SBO) and Artificial Neural Networks (ANN), both combined with the Genetic Algorithm (GA).

Figura 17 – Conceptual Model



Fonte: Elaborada pelos autores (2022).

SBO is a promising approach that combines the strengths of simulation and optimization, where the simulation model is used as the objective function of optimization, and the optimization technique is used to determine the optimal configuration of simulation parameters (KÜCK *et al.*, 2016). Combined with the GA it is possible to allow changes to the objective function, i.e., changes to the simulation model representing the real production system. Additionally, GA and ANN were the most applied and promising techniques to improve production scheduling, as investigated in the study by Takeda-Berger *et al.* (2020). Also, other studies addressing inventory control have also been successful in implementing the ANN (e.g., He, 2013; Hsu; Lin; Chien, 2015; Zhang; Wang; Li, 2019). Such a fact can be justified by the ability ANN has to learn in a given environment and improve performance, generating predictions quickly (NEMIROVSKY *et al.*, 2018).

Thus, the goal of CM is to propose a predictive-reactive production scheduling based on inventory data from the shop floor to deal with material non-availability during production execution. To achieve this, firstly, the shop floor environment should be considered consistent with Industry 4.0 practices, with sensor-equipped collaborating machines, enables the collection of data about the current state of the system in real-time (WANG; TÖRNGREN; ONORI, 2015). Then, the CM can be integrated into the information technology (IT) architecture of the company and allow data exchange between the real system and the simulation model. The IT architecture can connect the model to the Enterprise Resource Planning System (ERP), Manufacturing Execution System (MES), Production Data Acquisition System (PDA), and/or the systems required to feed the data.

From this, predictive scheduling can be generated with a combination of ANN and GA. First, the ANN is trained to mimic the shop floor, using a set of input data (e.g., demand, inventory, priority rules, etc.) and output data (e.g., a given KPI). After that, combining with the GA, this optimization algorithm will test different combinations of dispatching rules (used to generate the schedule), to find the best scenario, according to the considered KPI. Thus, it is possible to obtain a better initial schedule, taking into account the one that obtains the best KPI.

Although predictive scheduling considers a better scenario, in the practical world ruptures can still occur during production execution. According to the proposed CM, the rupture considered is the non-availability of material (lack of inventory). To deal with this problem, the disruption triggers the reactive scheduling. Thus, reactive scheduling is generated from the combination of SBO and GA. This approach aims to provide an optimized set of dispatching rules to sequence the jobs on each machine on the shop floor.

This approach works as described as follows. To adapt the simulation model to the current state of the actual system, an adaptation function must be developed. This function will trigger an event-based adaptation, i.e., the simulation model is adapted to each event that occurs. When optimization is triggered, GA will begin to re-select for each individual machine the dispatching rule. GA will generate a population of possible solutions and use the simulation model to evaluate them. In this way, a possible set of dispatching rules will be determined by GA and introduced into the simulation model. The simulation model will simulate this set and return the key performance indicator (KPI) of this executed simulation for optimization. The GA will run the optimization for a few generations until its termination criteria. Finally, the result of the SBO approach will be a set of dispatching rules more suitable to the current state of the shop floor, considering current material availability, and ensuring the continuation of production.

In summary, the proposed CM enables to deal with the challenging environment that occurs in practice, which is the inventory availability. The CM is generic and can be adapted to different industrial scenarios. Considering the SLR conducted and to the best of the authors' knowledge, no model was found that addressed predictive-reactive strategy for the context of Industry 4.0. Meaning, the integration of promising approaches/technologies based on real-time collected data to feed the system, reacting and providing a feasible scheduling solution to maintain production stability, according to the required KPI.

3.3.4 Future research directions

Highlights of future research directions are presented here based on the SLR. Most of the papers reviewed suggest that future research should continue to improve their proposed models (e.g., Al-Aomar, 2006; Glassey; Resende, 1988; Mesghouni; Rabenasolo, 2002) or did not provide any future research directions (e.g., Cataldo; Perizzato; Scattolini, 2015; Huang; Liao, 2012; Paprocka; Skołud, 2013). However, it is possible to highlight some opportunities for the development of future research:

- The use of a discrete-event simulation (DES) technique can provide a powerful analysis of different scenarios, allowing for a detailed evaluation of production planning before its real-application (BEN-AWUAH *et al.*, 2010). Thus, the development of new research that models production scheduling in different segments of industries, and considers the uncertainties inherent to these systems, could provide better solutions to decision-makers.
- The implementation of highly automated systems to provide adaptability and efficient utilization of available resources has been a challenge in current systems. In this sense,

the multi-agent method reveals an excellent performance in terms of production scheduling (BOZEK; WYSOCKI, 2016). Thus, new multi-agent approaches could be explored to validate the advantages of this method for a dynamic manufacturing system.

- According to Jimenez, Gonzalez-Neira e Zambrano-Rey (2018), adaptive algorithms are appropriate to be extended to the control of manufacturing systems. Thus, it is possible to explore some mechanisms to find a trade-off between the optimal performance and reactivity given by the control system, such as multi-objective metaheuristics or artificial intelligence methods.
- Considering the Industry 4.0 context, new perspectives for future studies should be developed since decentralized decisions can be made based on flexibility on the shop floor, especially when disturbances occur (HERRERA *et al.*, 2016). Furthermore, the introduction of machine learning techniques can allow the system to "learning while doing" from the revealed data of the previous periods, and can determine the sequential decision making for the current scheduling (NING; YOU, 2018).
- Finally, as discussed in the previous section, few studies have addressed the integration of production scheduling with inventory in the short-term. Notably, few researches have adopted the predictive-reactive strategy. Thus, a CM was proposed in section 3.1.3.3 that aims to contribute to this gap by increasing the field of scientific knowledge as well as providing a new approach for practical implementation. As a next step, the CM can be tested and validated.

3.3.5 Final considerations

This paper conducted a SLR and, afterwards, proposed a conceptual model. The SLR confirmed that there is a dearth of approaches surrounding the integration between inventory control and production planning and control in the short-term. This study has contributed to fill this gap by proposing a CM for predictive-reactive production scheduling strategy based on inventory availability.

For the scientific community, the CM presents a method not previously adopted, i.e., it integrates inventory with production scheduling in the short-term. Moreover, the CM addresses promising technologies in the context of Industry 4.0. In practical terms, CM is able to support decision-making for owners and managers with the predictive-reactive scheduling strategy considering the uncertainties of inventory availability. This approach seeks to provide stability in production execution and a good KPI for the manufacturing context. Future research could develop the CM with the implementation of the suggested techniques. Thus, it will be possible to replicate the CM and evaluate its efficiency applying real manufacturing data.

A limitation of this paper is regarding the exact terminology used for the literature search. Some papers relating to production scheduling and inventory may been missed. Additionally, as the SLR followed the stages of the ProKnow-C technique, the bibliographic search was restricted to the criteria determined in subsection 3.3.2.1. Despite the limitations, our study contributes both to the scientific and managerial fields.

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CAPÍTULO 4
4 FASE 2

Neste Capítulo será apresentado o estudo que compôs a Fase 2 desta tese, com o objetivo de construir um modelo computacional com base no modelo conceitual apresentado na Fase 1 e ilustrá-lo por meio de um caso teste.

4.1 REACTIVE PRODUCTION SCHEDULING APPROACH BASED ON INVENTORY AVAILABILITY

Esta subseção apresenta o Artigo[4] 2, o qual foi apresentado no *10th IFAC Conference on Manufacturing Modelling, Management and Control (MIM 2022)* e está em processo de publicação no *IFAC-PapersOnLine*.

Abstract: Most manufacturing systems deal with dynamic environments where unpredictable events in real-time can cause a change in scheduled plans. Thereof, production scheduling is a decision-making process whose objective is to allocate limited resources to activities in order to optimize the production system. Thus, the development of an adaptive approach can improve efficiency and control of operations. This paper proposes a new reactive production scheduling approach based on inventory availability. Therefore simulation-based optimization is used to optimize job sequencing decisions in reaction to the current inventory availability. The approach is evaluated considering a real-world scenario based on an automotive component manufacturing company. As a result, the evaluation shows that this approach is able to deal with stochastic events and react to systems disruptions and improves the performance of the production system for the key performance indicator considered.
Keywords: Reactive scheduling, inventory, simulation-based optimization, data-driven, Industry 4.0.

4.1.1 Introduction

Production scheduling is one of the most important functions in a production company and has a significant influence on the performance of manufacturing systems (FRAZZON; KÜCK; FREITAG, 2018; REBOIRO-JATO *et al.*, 2011). Besides, production scheduling systems are necessary to determine when a job needs to be processed, using which machine to process, or which priority is assigned to the job (VALLEDOR *et al.*, 2018). The goal is to

[4] TAKEDA-BERGER, S. L.; AGOSTINO, Í. R. S.; SILVA, M. R. F. d.; FRAZZON, E. M. Reactive production scheduling approach based on inventory availability. Forthcoming: IFAC-PapersOnLine, 2022.

effectively utilize available resources to achieve relevant key performance indicator targets for the organization. However, production scheduling has some challenges due to dynamic and uncertain production environments, which can have disruptions such as machine breakdowns, material shortage or short-term changes (e.g., new orders arrival, cancellation of orders). In response to these challenges, scheduling frequently requires rescheduling of the jobs. Rescheduling is defined as the process of updating production scheduling that already exists as a response to disruptions that may occur (JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018).

Additionally, Berger, Zanella e Frazzon (2019) comment that there is a research opportunity related to production scheduling considering inventory availability as a disruption. In the literature, the most frequently discussed disruption has been machine breakdowns (PETROVIC; DUENAS, 2006). Alongside to high due-date reliability, short throughput times and high resource utilization, low inventories represent the fourth important goal of Wiendahl's logistic goal system (WIENDAHL, 2014). Inventory is needed to avoid shortages or surpluses, and thus production execution will not be obstructed (WIDYADANA; WIDJAJA; LIONG, 2017). Although inventory planning is traditionally considered as an individual task separate from production scheduling and control, there are approaches to integrate both tasks (KUMAR; TIWARI; GOSWAMI, 2016; MUNGAN; YU; SARKER, 2010). Besides, Frazzon *et al*. (2020) point out that inventory planning is an important strategy to obtain integration in manufacturing systems.

Accordingly, production scheduling problems require decision-making involving optimization of one or more scheduling criteria (FRAZZON; ALBRECHT; HURTADO, 2016). Since most production scheduling problems are complex and stochastic, it is not always possible to find an optimal solution in a reasonable period of time, and computational difficulties arise for most optimization techniques (NGUYEN; MEI; ZHANG, 2017). Hence, many heuristics have been presented in the literature to find quasi-optimal solutions in a relatively short time. Most frequently applied heuristics in practice are dispatching rules used to prioritize all pending jobs in the queue to be processed by a machine (FREITAG; HILDEBRANDT, 2016). Among the advantages of using dispatching rules, it is possible to highlight its easy implementation, low computational complexity, and also the short time required to achieve good solutions (VIEIRA *et al*., 2017). After a system state has changed due to a disruption on the shop floor, scheduling with the selected dispatching rules may be inefficient in the new situation (FRAZZON; KÜCK; FREITAG, 2018). Thus, traditional production scheduling approaches are not able to incorporate dynamic changes in the system into optimization.

In this context, this paper proposes a new reactive production scheduling approach based on inventory availability, using simulation-based optimization to optimize job sequencing decisions in reaction to the current inventory availability. The remainder of this paper is structured as follows: In Section 4.1.2 related work is presented to support the research. Section 4.1.3 describes the proposed approach in detail. In Section 4.1.4 the approach is evaluated by a test case of a job shop production environment. The paper closes with a conclusion and an outlook.

4.1.2 Related work

Traditionally, methods have been developed to design and optimize production scheduling. Janak *et al*. (2006) presented a reactive scheduling framework which provides an immediate response to unexpected events such as machine breakdown or the addition or modification of orders. For that, the proposed mathematical framework utilizes a mixed-integer linear programming (MILP) developed for short-term scheduling problems with modifications introduced to reflect the effects of the unexpected event. Additionally, the framework proposed by Agostino *et al*. (2020) studies an approach to automatically synchronize the planning and control of production according to the current state of the shop floor. The proposed approach utilizes a digital twin of the production system to optimize the use of dispatching rules for each machine in the system every time a stochastic event is identified, allowing a constant update in the process.

Pan, Liao e Xi (2012) proposed an integrated prognostics-based-scheduling model, incorporating both production scheduling and predictive maintenance planning for a single machine to minimize the maximum tardiness. Also, in a scenario of a single machine, Ladj, Varnier e Tayeb (2016) proposed a genetic algorithm (GA) with the objective of minimizing the total cost of repairs on a machine submitted to predictive maintenance. Hasan, Sarker e Essam (2011) also used GA in their research, but in a job-shop scheduling context considering machine breakdowns and unavailability. The aim of this paper was to recover the system from interruptions during the initial stage of schedules.

Although the analytical methods are efficient to conduct production scheduling, the solutions proposed for optimization are overloaded with limitations due to the dynamic nature of manufacturing and the high complexity of mathematical programming. In this direction, the systematic literature review performed by Uhlmann e Frazzon (2018) identified as research opportunities the use of optimization algorithms based on simulation to evaluate and reschedule production using practical application in real industries. Thus, the simulation-based optimization (SBO) is a promising method that combines the strengths of simulation and optimization, where the simulation model is used as the objective function of optimization, and the optimization technique is used to determine the optimal configuration of simulation parameters (KÜCK *et al.*, 2016). Frazzon *et al.* (2018), proposed a hybrid approach to integrate production scheduling and transportation processes along supply chains. The authors integrated GA with SBO to evaluate scheduling through an automated procedure and obtained a significant reduction of late orders.

Although the reviewed authors achieved efficient results, their researches have some limitations. First of all, to the best of our knowledge, none of the authors integrated production and inventory availability in the model. Also, some studies, such as Pan, Liao e Xi (2012) and Ladj, Varnier e Tayeb (2016), considered a single machine scenario. Thus, this paper aims to fill these gaps by proposing an approach implementing the SBO to generate a reactive production schedule based on inventory availability. The approach is expected to mitigate backlogs in production jobs by proposing adjusted schedules based on the reality of the shop floor.

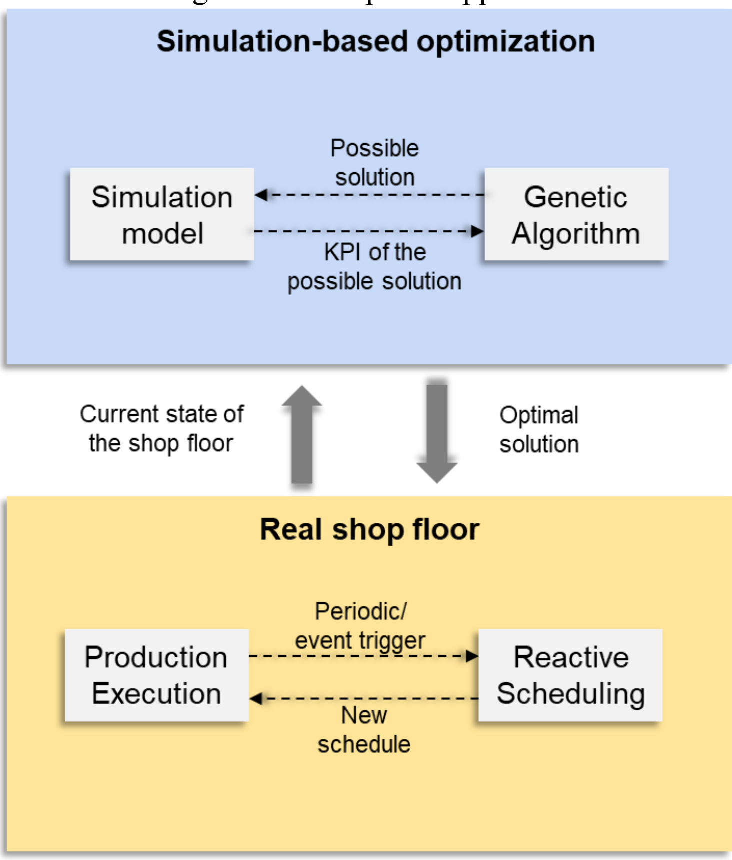
4.1.3 Proposed approach

This section firstly describes the proposed approach. Subsequently, the framework for data exchange between the approach and a manufacturing execution system (MES) for shop floor control is presented.

4.1.3.1 Reactive production scheduling approach based on inventory availability

The proposed approach for reactive production scheduling based on inventory availability is shown in Figure 18. This proposal is based on the paper by Frazzon, Kück e Freitag (2018) and on the conceptual model by Berger, Zanella e Frazzon (2019). Thus, through the SBO implementation, it aims to provide a reschedule, i.e., optimized set of dispatch rules to sequence jobs on each machine, in reaction to inventory non-availability.

Figura 18 – Proposed approach



Fonte: Elaborada pelos autores (2022).

In order to respond to real-time disruptions, an SBO combined with a GA is applied. An adaptive simulation-based optimization is a hybrid method combining the technical features of simulation and optimization, in order to obtain a solution more adherent to reality, without disregarding the mathematical sense (BERGER; FRAZZON; DANIELLI, 2018; FRAZZON *et al.*, 2018). GA is described as a robust optimization technique that mimics nature's evolutionary process (TAKEDA-BERGER *et al.*, 2020). This technique aims to optimize a specific problem representing its solutions through a population of restricted size containing viable solutions, that will be considered as individuals of the population. These individuals will collectively and iteratively evolve into new viable solutions (JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018). GA allows changes of the objective function, i.e., changes of the simulation model representing the real production system. The combination between the simulation model and the GA enables the objective function of optimization heuristic to become a function of the simulation output (e.g., number of tardy jobs, mean throughput time, utilization).

According to the proposed approach, Figure 18, to adapt the simulation model to the current state of the actual system, an adaptation function was developed. This function triggers an event-based adaptation, i.e., the simulation model is adapted to each event that occurs. When optimization is triggered, GA will begin to re-select for each individual machine the dispatching rule, and it will generate a population of possible solutions and use the simulation model to evaluate them. Then, a possible set of dispatching rules will be determined by GA and introduced into the simulation model. The simulation model will simulate this set and return the KPI of this executed simulation for optimization. The GA will run the optimization for a few generations until its termination criteria. Finally, the output of the SBO method is a set of most suitable dispatching rules for the current state of the shop floor, mitigating the disruptions of the production.

Equation (1) presents the adaptation function developed. This function A determine whether, for a particular point in time *t*, the state of the simulation model S_{sim} represents the state of the real manufacturing system S_{true} (A=0). If not, it has to be adapted (A=1) and a new optimization run has to be conducted. Function A triggers an adaptation periodically as well as event-based, i.e., the simulation model is adapted every p period as well as for certain events (in this paper was considered the inventory level).

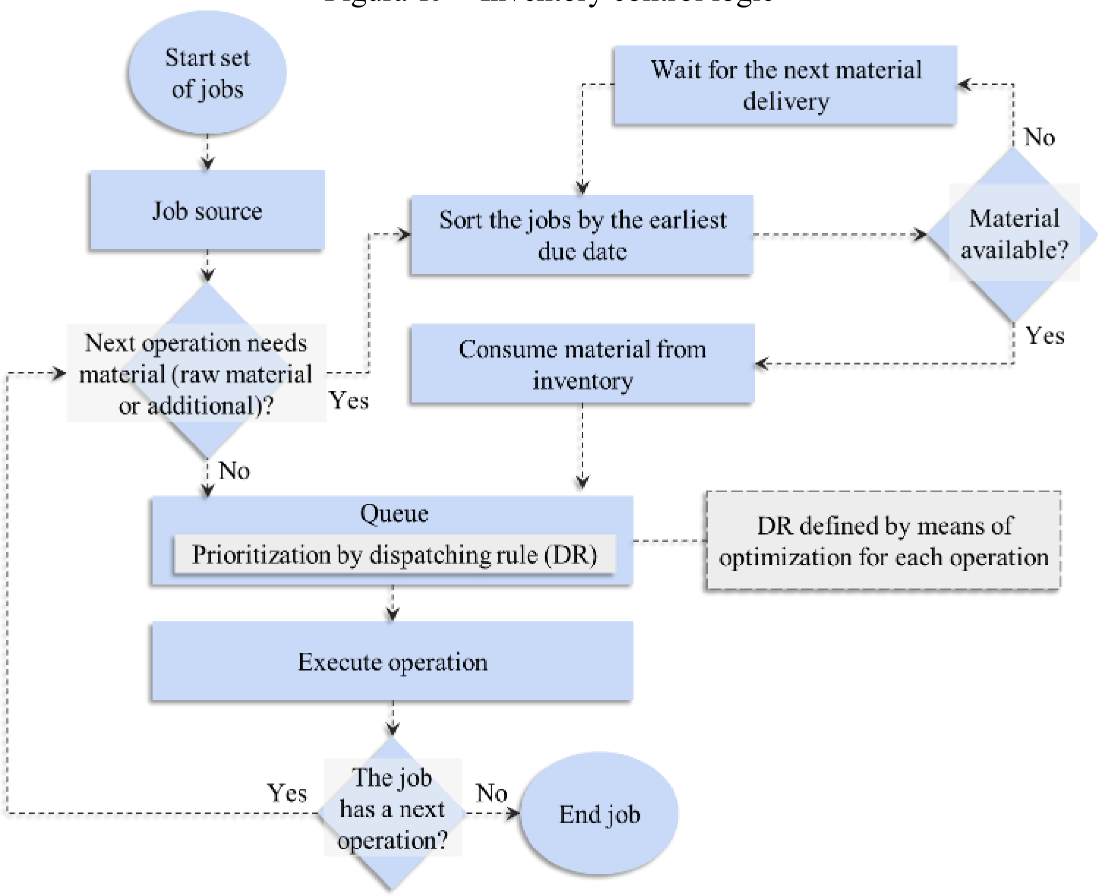
$$A_{periodic+event}\big(S_{true}(t), S_{sim}(t)\big) = \begin{cases} 1, t = kp, k \in \mathbb{N} \\ 1, D_I\big(S_{true}(t), S_{sim}(t)\big) > z \\ 0, else. \end{cases} \tag{1}$$

The trigger event is inventory change I. D_I represents the difference in the inventory level between the real system and the model, i.e., new arriving raw material. The value for *z* is one batch of raw material, and the value for *k* is considering one month.

The inventory control logic is shown in Figure 19. In this logic, after a set of jobs has been released into the system, the first decision is to check whether the next operation needs additional material or raw material to be started. In case it not requests, the job is queued for the next operation. The set of jobs that require material is sorted by their due dates. This process ensures that the jobs with highest priority will use the available material first if one or more jobs compete for the same material. Then, for each job, the availability of the required material is checked. If the material is available, the job consumes its material and is enqueued. In case the required material is not available, the job is sent to a waiting process until the next material delivery. On a delivery, all blocked jobs in the waiting process are released and sorted again to check material availability for the new inventory levels available.

The operation processing is started whenever a machine and the necessary material are available. Then all jobs in the queue are sorted using a dispatching rule and the jobs with the highest priority is started. The rule is defined by the optimization engine.

Figura 19 – Inventory control logic



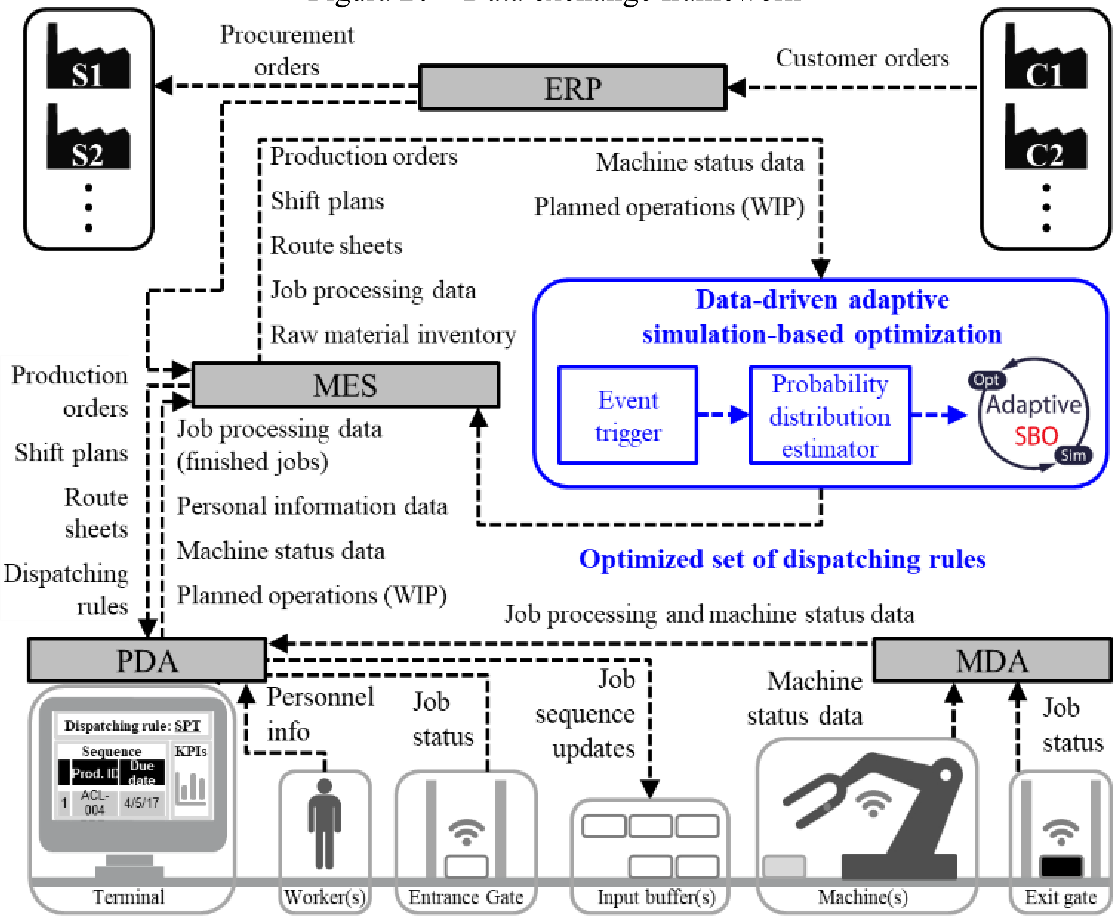
Fonte: Elaborada pelos autores (2022).

When the operation execution finished, the logic checks whether the current job is finished or has one or more operations to execute. In the latter, the inventory control logic will perform the same steps again to manage the inventory consumption for the next operation of the job.

4.1.3.2 Data-exchange framework

In order to enable the integration of the proposed approach to the information technology (IT) architecture of an enterprise, the framework proposed by Frazzon, Kück e Freitag (2018) was adapted, which allows the exchange of data between the real system and the simulation model (Figure 20). The framework comprises four main systems: an enterprise resource planning system (ERP), a manufacturing execution system (MES), a production data acquisition system (PDA), and a machine data acquisition system (MDA).

Figura 20 – Data exchange framework



Fonte: Adaptada de Frazzon, Kück e Freitag (2018).

The ERP system manages the planning of jobs such as production orders, shift plans, route sheets for different products. The PDA is responsible for the collection of data about the shop floor processes, gathering information such as personal information, the current state of planned operations and job processing data and machine status data from the MDA. MES, the central element of this structure, receives continuous updates of the data from the ERP and PDA systems, storing and providing it as input for the proposed approach. The MES is also responsible for the execution of the reactive scheduling, triggered periodically and by event. Therefore, the MES applies the result obtained, i.e., the dispatching rules recently selected to maintain the execution of the jobs on the shop floor.

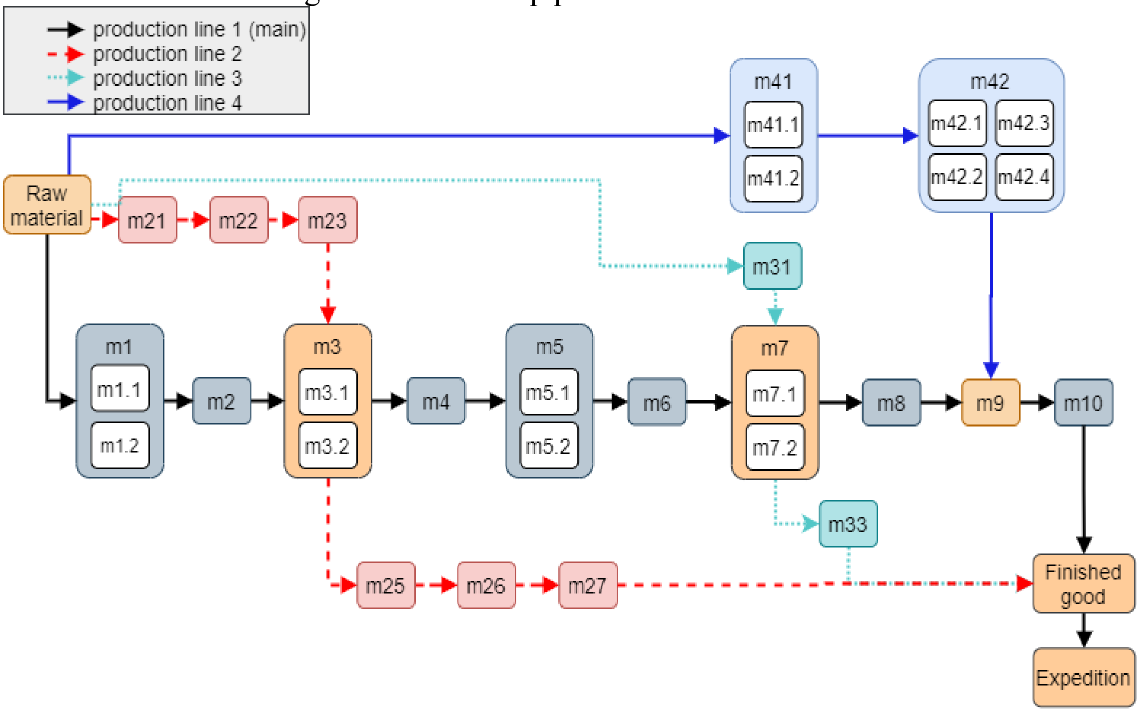
4.1.4 Test case

This section is structured as follows: First the scenario is described, then the parameters used in the experiment, as well as the KPI considered. Subsequently, a description is provided on how the approach was implemented. Finally, the section closes with the results and an analysis of the test case.

4.1.4.1 Test case presentation

The approach was evaluated in a job shop production environment. The shop floor and data were based on a mechanical component manufacturing company in southern Brazil. The scenario is shown in Figure 21 and is the same presented by Agostino *et al*. (2020). The horizontal main line (black) has two workstations with parallel machines (orange) which are shared by jobs from two other lines (red, dashed and green, dotted). The fourth line (blue) produces parts that are assembled with parts of the main line. The whole scenario contains 20 workstations, which group 28 individual machines. Each workstation has between one and four machines and is grouped by a box in the figure.

Figura 21 – Job shop production environment



Fonte: Adaptada de Agostino *et al*. (2020).

4.1.4.2 Experiment description

The scenario was implemented and simulated in AnyLogic 8 Personal Learning Edition 8.5.2. The experiment was executed in a stochastic environment, which includes variations in the processing and setup times and stochastic inventory availability. The processing and setup times were defined based on the historical data provided by the company and multiplied by a stochastic factor using a triangular distribution.

The optimization used the GA package in R 3.6.3 language (TEAM, 2013). This particular implementation of GA is fully open source and available for scientific reproducibility purposes, and published in the Journal of Statistical Software (SCRUCCA, 2013). The package offers easy integration of GA with other external applications using the R language as an open-source tool with recognized statistical and scientific validity. The optimization was defined with the following parameters: a population of 40 individuals with a mutation rate of 10%, and crossover rate of 80%. As termination criteria was defined 3 rules: (*i*) after three consecutive generations without any improvement in the best fitness value; (*ii*) if the fitness value reaches the minimization limit (in this case, the minimum possible value for the number of tardy jobs is zero); or (*iii*) after the maximum number of 5 generations. The definition of the termination criteria took into consideration the tests applied in the development of the experiments, as well as the literature consulted (AGOSTINO *et al.*, 2020). If one of these criteria is reached, the GA stops and the best solution (optimal set of dispatching rules) is chosen. The previous tests showed that few interactions were enough to find good results in a reasonable computation time.

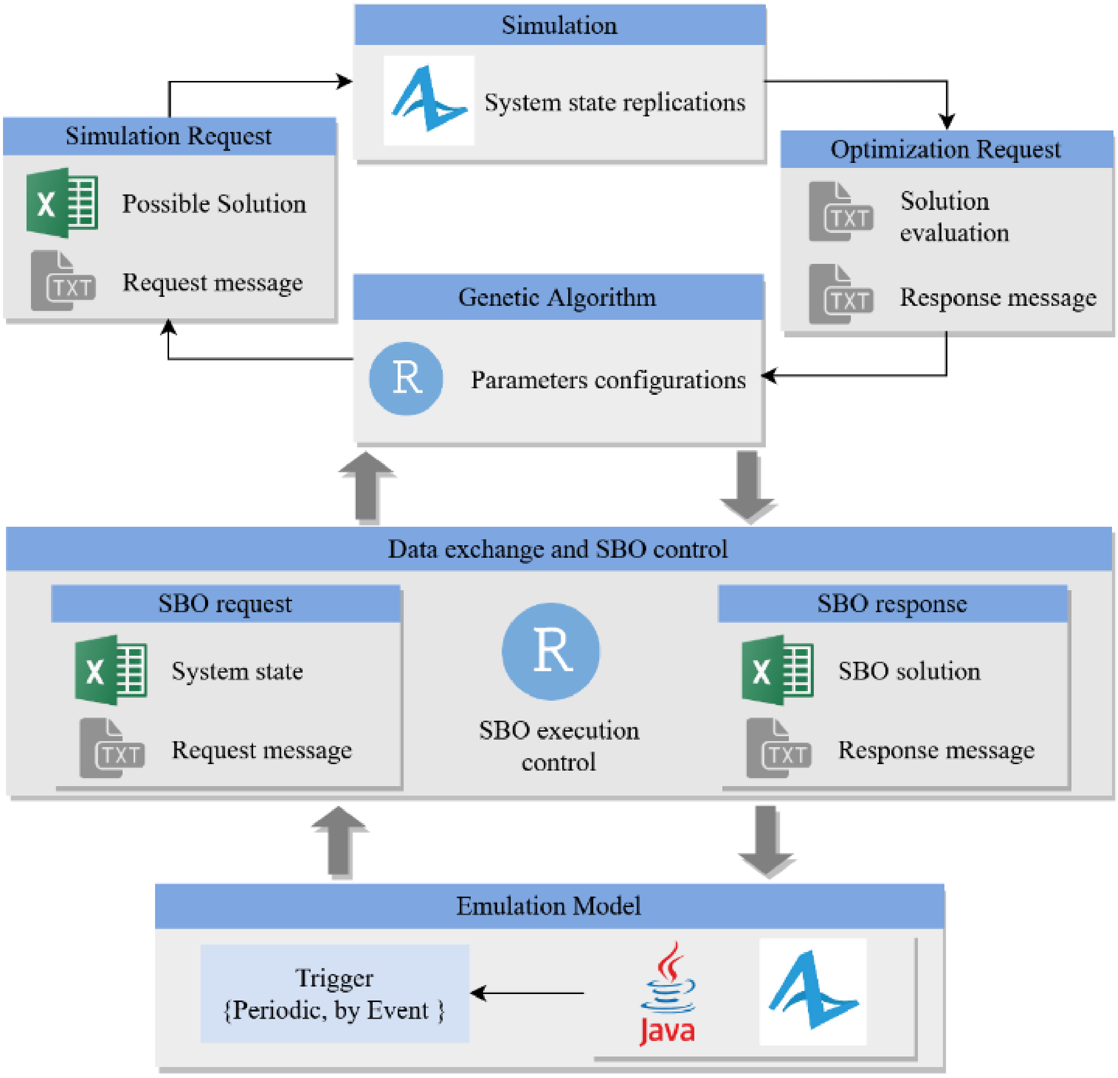
The approach was tested to find an optimized set of dispatching rules considering both triggers: per period, i.e., every beginning of the month, and per event, which were considered material delivery every three months. Thus, the experiment simulated 15 months of operations for each run based on real demand provided by the company. Henceforth, were executed 1800 different simulation runs, guided for the evolutionary optimization strategy provided by the GA implementation.

Finally, the dispatching rules applied in this experiment were based on the results by Frazzon, Kück e Freitag (2018): (1) Earliest Due Date (EDD); (2) Modified Due Date (MDD); (3) Operational Due Date (ODD); (4) Shortest Processing Time (SPT); and (5) Least Global Slack (SLK). At the end of the experiment, the performance of the proposed approach is evaluated by means of the number of tardy jobs. As each job has a due date, a job becomes tardy if it finishes after its due date. Thus, this performance was compared against five benchmark scenarios that use a static set with the same dispatching rule for each machine and also, the current strategy of the company that uses a fixed production schedule for the production execution.

4.1.4.3 Implementation

The implementation of the approach uses two environments. The simulation model was implemented in AnyLogic using a discrete event simulation (DES). AnyLogic is a java-based simulation tool that allows to use graphical tools and code implementation in Java for a specific process. The optimization was implemented in R that provides a flexible set of models for evolutionary optimization (SCRUCCA, 2013). The integration between these two software was implemented as a control logic algorithm in R. Figure 22 shows the communication process of the approach, and it operates as follows. The real production system is emulated by a simulation model in AnyLogic. The adaptation function that triggers the SBO method is integrated with the emulation model. If a condition of the adaptation function is met, a request message is sent by the emulation model. This is read by the control algorithm in R and it initializes the GA with the defined parameters and current system state data. After that, a second simulation model is used to evaluate each individual of the GA in a determined number of replications.

Figura 22 – Communication process



Fonte: Elaborada pelos autores (2022).

The interaction between the simulation model and the GA is conducted using a data exchange logic based on sending and receiving a set of files with the solutions and the quality evaluation of the individuals. A number of generations evolve until one of the termination criteria are met; thus, an optimal solution is generated for a specific state of the production system. Finally, the control algorithm sends the optimal solution to the production system and the emulation model reads and applies this solution to continue operations.

4.1.4.4 Results and analysis

The proposed approach was implemented to optimize the due date adherence in terms of the number of tardy jobs, which is the most important KPI of the company in this research. However, it is possible to use a different optimization KPI since the approach provides flexibility to changes. Table 2 shows the results of the implementation, comparing the approach against the performance of other scenarios. The approach achieves a significantly better performance than the current strategy of the company, a fixed schedule, presenting a lower amount of the number of tardy jobs (30% better).

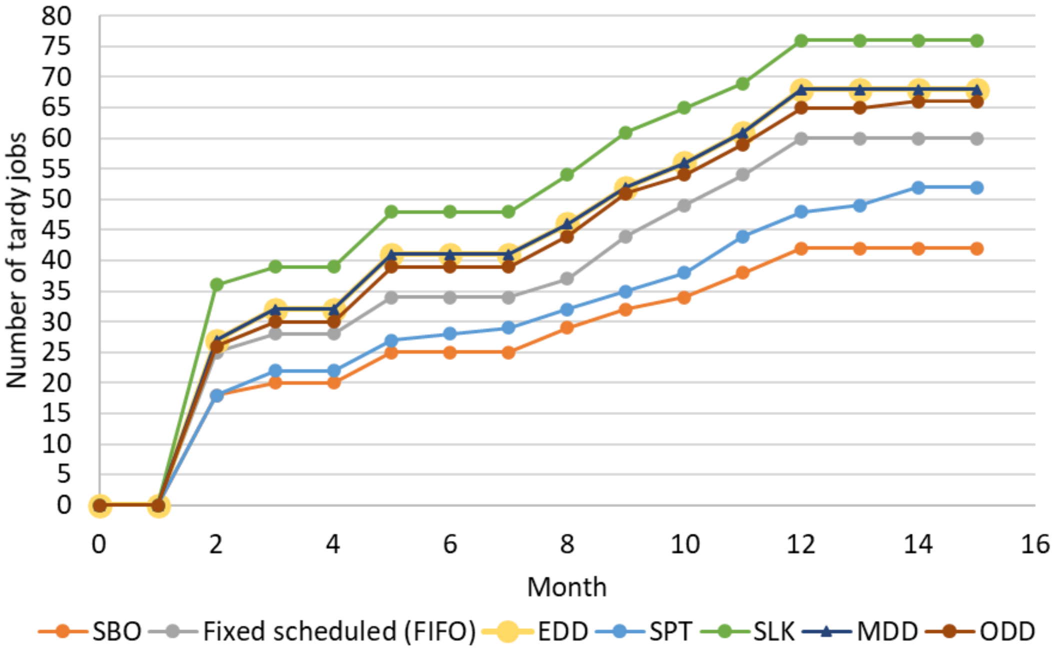
Tabela 2 – Approach performance comparison

Approaches	**Number of Tardy Jobs (TJ)**	**TJ comparison over fixed schedule**
Fixed Schedule (FIFO)	60	-
Reactive scheduling (SBO)	42	-30%
SPT	52	-13%
ODD	66	+10%
EDD	68	+13%
MDD	68	+13%
SLK	76	+27%

Fonte: Elaborada pelos autores (2022).

Furthermore, the approach also performs better against static, identical dispatching rules as it determines the suitable dispatching rule for each machine based on the current state of the manufacturing system. Figure 23, shows the cumulative tardy jobs evolution over the 15 months for the different scheduling approaches.

Figura 23 – Tardy jobs evolution comparison



Fonte: Elaborada pelos autores (2022).

In summary, the proposal achieves the best overall results as it outperforms the other scenarios on average. Hence, it is able to deal with stochastic events such as inventory disruptions in real-time, generating a reactive schedule, while the strategy currently applied in the company lacks this ability.

4.1.5 Conclusion and outlook

This paper proposed a new reactive production scheduling approach based on inventory availability. For this, the approach used a simulation-based optimization to provide reactive scheduling to inventory disruption, with an optimized set of dispatching rules to sequence the jobs on each machine in a job shop. The objective of the approach is to serve as a generic model for implementation considering inventory availability using an SBO solution in dynamic production systems. As a result, it achieves the best overall results since it outperforms the other scenarios on average. A limitation of this research is that the approach was evaluated based on a specific scenario with data from the industry. In addition, other system disruptions were not considered, as the aim was to evaluate the system's reaction considering material availability. Thus, as future research, other companies, as well as different company sizes, can be considered different scenarios. Furthermore, other disruptions in the system can be included, such as machine breakdowns, the arrival of new orders or cancellation of orders. Moreover, as a contribution of this paper, the approach is able to support decision-making for owners and managers with the reactive scheduling caused by the non-availability of material, mitigating the impact on the chosen KPI for the manufacturing context.

Acknowledgements

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CAPÍTULO 5

5 FASE 3

Neste Capítulo será apresentado o estudo que compôs a Fase 3 desta tese, com o objetivo de analisar o desempenho do modelo proposto em um estudo de caso.

5.1 AN INVENTORY DATA-DRIVEN APPROACH FOR PREDICTIVE-REACTIVE PRODUCTION SCHEDULING

Esta subseção apresenta o Artigo[5] 3, contemplando o resultado final desta tese de doutorado. Este artigo está em fase de submissão.

Abstract: Effective production scheduling is at the heart of an efficient manufacturing process and can result in on-time product delivery, improved quality, reduced inventory costs, and increased productivity. However, scheduling is a complex task due to the need to optimize multiple competing objectives and react to unpredictable events that may occur during production execution. The strategy of predictive-reactive scheduling can be used to reconcile the conflict between the original schedule and the current shop floor situation while maintaining production continuity and good quality scheduling. Furthermore, with digital advances in manufacturing environments, data-driven approaches have been explored to provide more efficient resource allocation. In this context, this study seeks to present an inventory data-driven predictive-reactive production scheduling approach that supports the evolving concepts of the fourth industrial revolution. Periodically, the combination of a machine learning technique, Artificial Neural Network (ANN), and Genetic Algorithm (GA) provides predictive scheduling considering a best-case scenario according to an established Key Performance Indicator (KPI). Then, with real-world dynamics, material non-availability causes disruptions in production, which triggers the simulation-based optimization (SBO) method to handle these events. Thus, SBO provides a reactive schedule with the best set of priority rules to sequence jobs on each machine according to the data on the shop floor. This proposed approach was validated through computer simulation with a real case study using data collected from a metal-mechanical company. Considering the service level KPI, the results showed that the approach is able to find a better solution in the compared scenarios. Therefore, even in a dynamic and stochastic scenario, with machine breakdowns, quality problems, raw material delays, and accuracy issues, the approach proved efficient in mitigating these variations' effects. This study contributes threefold. First, the combination of methods adopted is unique in the literature. Second, the approach improves the understanding of the problems inherent in material non-availability by reducing the information uncertainty and providing knowledge about the shop floor data. Third, it allows decision-making to be faster and smarter, presenting solutions that improve the manufacturing system's operational efficiency and promoting companies' competitiveness.

Keywords: Production scheduling. Predictive-reactive. Inventory. Machine learning. Simulation-based optimization. Data-driven.

[5] TAKEDA-BERGER, S. L.; FRAZZON, E. M. An inventory data-driven approach for predictive-reactive production scheduling. Working paper, 2022.

5.1.1 Introduction

Production scheduling has been a focus of research for decades, especially because it is a fundamental function of manufacturing systems and presents a complex decision-making procedure. The complexity of production scheduling is because it is a process to optimize the allocation of available resources to execute tasks in a defined period, according to production restrictions (QIAO; LIU; MA, 2021). Therefore, performing an efficient production scheduling is crucial for manufacturing, as it must deliver products or services to customers promptly (JIANG *et al*., 2021). However, real production scheduling in practice embraces changes or updates driven by internal or external problems (UHLMANN; ZANELLA; FRAZZON, 2022). Some of these inevitable changes that may occur over time during the process are machine breakdowns, material non-availability, and short-term changes (e.g., new order arrivals or order cancellations), among others (SCHUH *et al*., 2017). Thus, production rescheduling is required to update the initial schedule in response to these changes (UHLMANN; FRAZZON, 2018).

Some research has described different strategies adopted in production scheduling (CHAARI *et al*., 2014; DIAS; IERAPETRITOU, 2016; HERRERA *et al*., 2016; JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018). However, the predictive-reactive scheduling strategy is the most commonly used strategy in manufacturing systems (OUELHADJ; PETROVIC, 2009; VIEIRA; HERRMANN; LIN, 2003). In general, predictive-reactive scheduling has two phases: in the first, decision-making techniques are conducted before the beginning of the execution, and in the second, decision-making techniques are conducted during the production execution (JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018). While the first phase generates a predictive schedule, the second phase generates a reactive schedule aiming to repair the initial schedule by reacting to disruptions.

The generation of the schedule can occur in two ways. The first is by calculating the complete production schedule, and the second is by using priority rules to continuously calculate the priorities of all jobs in the queue waiting to be processed (FRAZZON; KÜCK; FREITAG, 2018). Calculating the complete schedule can be very time-consuming, as it would require incorporating many parameters. Moreover, schedules may become obsolete due to stochastic effects, such as changes in processing time and due dates (KÜCK *et al*., 2017). Nevertheless, considering industrial practice, scheduling only needs to capture a global picture of resource contention and give relative priorities to jobs (AYTUG *et al*., 2005). Thus, priority rules present a feasible solution, being easy to implement in practice, efficient execution time, and allowing for quasi-optimal solutions for special cases (VALLEDOR *et al*., 2018; ZHANG; JIANG; GUO, 2009). Moreover, priority rules are considered a primary approach for reactive scheduling (BOŻEK; WYSOCKI, 2016).

Takeda-Berger *et al*. (2022a) conducted an extensive literature review. They identified some research on the predictive-reactive production scheduling strategy (e.g., ABU; YAMADA; TERANO, 2010; AKKAN, 2015; BOŻEK; WYSOCKI, 2016; HAUPTMAN; JOVAN, 2004; JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018; PACH *et al*., 2014; SUN; XUE, 2001; VALLEDOR *et al*., 2018). Among the portfolio of papers analysed, it was found that this strategy remains under-explored, which provides opportunities for new research. Furthermore, most studies addressed the predictive-reactive strategy to deal with machine breakdowns (BARTÁK; VLK, 2015; KALINOWSKI; KRENCZYK; GRABOWIK, 2013; TANG; WANG, 2008).

However, inventory availability is a critical issue in manufacturing systems. The COVID-19 pandemic exposed the criticality of inventories since the world economy still faces a negative supply inventory, as many factories had to close, disrupting the global supply chain network (CHOWDHURY *et al*., 2020). Nevertheless, there is a trade-off relating to inventory, as material non-availability can significantly affect the system's productivity, while excessive inventories increase the cost of operation (JIANG *et al*., 2011). In addition, high inventories result in freezing a company's capital as well as investment for storage locations, which may hinder investment strategies that exploit the benefits of economies of scale (SUSARLA; KARIMI, 2018). Frazzon *et al*. (2020) highlight that inventory planning is an important strategy for integration in manufacturing systems. Although inventory is traditionally considered an individual task separate from production planning and control (PPC), there are some efforts to integrate both (KUMAR; TIWARI; GOSWAMI, 2016; PAN *et al*., 2015; RODRIGUEZ *et al*., 2018; SANA, 2011), but mainly with a focus on long-term planning decisions. Hence, there is still a research gap that integrates inventory data with production scheduling, i.e., production scheduling reacting in real-time in response to the disruption of material non-availability (BERGER; ZANELLA; FRAZZON, 2019).

Additionally, new opportunities for studies have emerged through the significant changes that the fourth industrial revolution (also called Industry 4.0) has been generating in manufacturing systems. Industry 4.0 defines a methodology to transform machine-dominant manufacturing into digital manufacturing (OZTEMEL; GURSEV, 2020). Leusin *et al*. (2018) comment that this methodology involves the combination of intelligent and adaptive systems with shared knowledge between heterogeneous platforms for computational decision-making within cyber-physical systems (CPS). Therefore, multiple sensors and sensing techniques are introduced to capture information between manufacturing entities on the shop floor and across the company, promoting better communication (MONOSTORI *et al*., 2016). This CPS vision provides new solutions to industrial problems as it integrates computational with physical processes and considers the real-time state of the system, supporting better decision-making (FRAZZON *et al*., 2020).

Consequently, a huge amount of data is generated along all manufacturing processes. Thus, the early enthusiasm for artificial intelligence and machine learning did not achieve their intended purpose in the past but is now realized with the advent of Industry 4.0 transformational technologies (ELMARAGHY *et al*., 2021). Digital technologies do not only enable data-driven decision support tools (DUAN; EDWARDS; DWIVEDI, 2019; FRAZZON; KÜCK; FREITAG, 2018) but also stimulate the development of new research on learning mechanisms – or machine learning (ML) techniques – to improve the solution generation capacity of systems (PINEDO, 2016). Besides this motivation to use ML techniques, the simulation-based optimization (SBO) approach is also becoming notable for decision support. It is considered a powerful tool for solving stochastic and complex problems, such as the manufacturing environment (LIN; CHEN, 2015). SBO combines the strengths of simulation and optimization, whereby the simulation model is used as an objective function of the optimization, and the optimization technique is used to determine the optimal configuration of the simulation parameters (KÜCK *et al*., 2016).

Considering this exposed context, this study aims to propose an inventory data-driven approach for predictive-reactive production scheduling. Periodically, the combination of Artificial Neural Network (ANN) and Genetic Algorithm (GA) provides predictive scheduling considering a best-case scenario according to an established Key Performance Indicator (KPI). Then, with real-world dynamics, material non-availability causes disruptions in production, which triggers the SBO approach to handle these events. Thus, SBO provides a reactive schedule that is an optimized set of priority rules to sequence the jobs on each machine according to the data on the shop floor. The proposed approach was validated through computer simulation with a real case study using data collected from a metal-mechanical company.

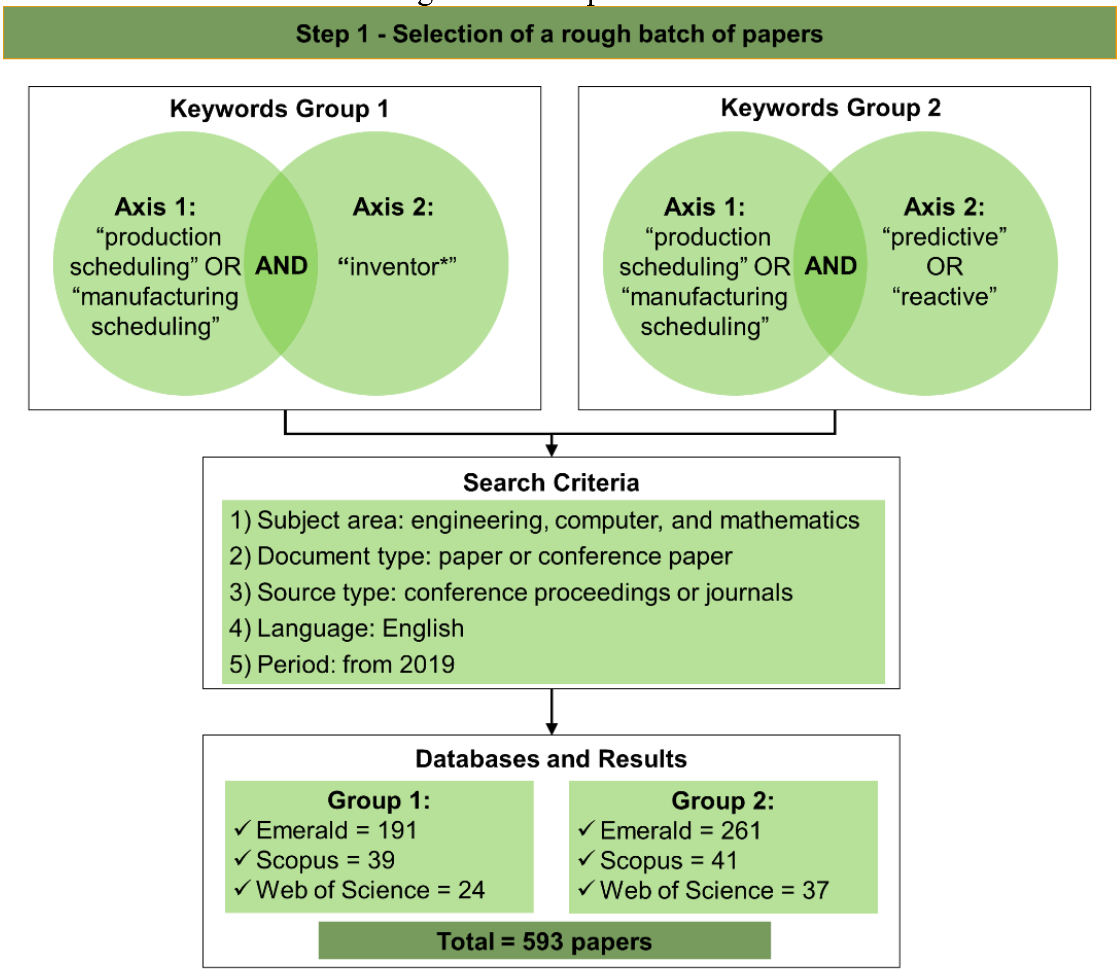
Considering the service level KPI, the results showed that the approach is able to find a better solution than the compared scenarios. Therefore, even in a dynamic and stochastic scenario, with machine breakdowns, quality problems, raw material delays, and accuracy problems, the approach proved efficient in mitigating these variations' effects. Some contributions of this study can be highlighted. First, to the best of our knowledge, the combination of methods adopted is unique in the literature. Second, the approach can also be of value by improving the understanding of the problems inherent in material non-availability, reducing information uncertainty, and providing knowledge about the shop floor data. In addition, it allows decision-making to be faster and smarter, presenting solutions that improve the manufacturing system's operational efficiency and promoting companies' competitiveness.

The remainder of this study is organized as follows. Section 5.1.5 presents a current literature review relevant to the topic addressed. Section 5.1.3 describes the proposed approach for predictive-reactive production scheduling, combining machine learning and SBO. Section 5.1.4 presents the case study conducted to validate the approach. The results are discussed in Section 5.1.5, and the theoretical and practical contributions are discussed in Section 5.1.6. Finally, Section 5.1.7 concludes the work by highlighting the knowledge obtained and encouraging future research opportunities.

5.1.2 Literature review

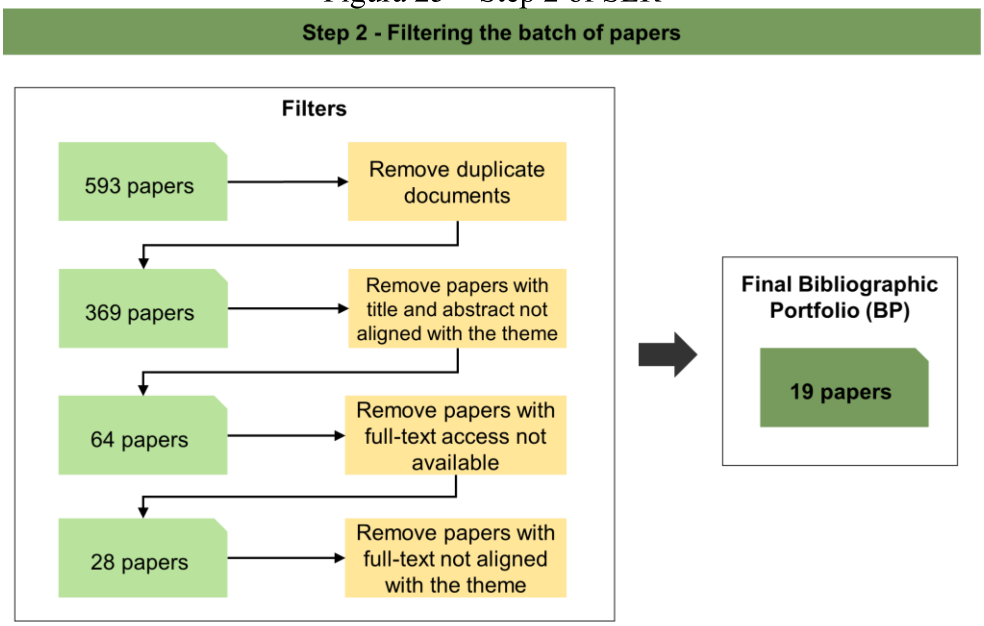
In this paper, an update of the literature review presented by Takeda-Berger *et al.* (2022a) was performed, as the authors conducted a very in-depth Systematic Literature Review (SLR) about the topic addressed here. Accordingly, this paper covers a continuation of the SLR from 2019, with the research conducted in August 2021. Figure 24 presents the first step of the SLR. In this step were defined the keywords and the search criteria in the databases resulted in a first rough batch of papers. Then, Figure 25 presents the second step of the SLR. Here, some filters were applied to the rough batch of papers in order to refine the selection of papers according to the studied topic. The result is a final Bibliographic Portfolio (BP) of 19 papers, which will be discussed as follows.

Figura 24 – Step 1 of SLR



Fonte: Elaborada pelos autores (2022).

Figura 25 – Step 2 of SLR



Fonte: Elaborada pelos autores (2022).

5.1.2.1 Production scheduling strategies

There has been increasing interest in modelling and solving scheduling problems in dynamic environments. In the real world, manufacturing systems face uncertainty due to unexpected events on the shop floor. To deal with this, scheduling should be an ongoing reactive process to real-time events, reconsidering and revising the pre-established schedule (BARTÁK; VLK, 2015).

Since the paper by Vieira, Herrmann e Lin (2003), the literature on production scheduling has been outlined resulting from the proposed framework on production rescheduling (AYTUG *et al.*, 2005; OUELHADJ; PETROVIC, 2009; PAPROCKA; KRENCZYK; BURDUK, 2021). According to Vieira, Herrmann e Lin (2003), two rescheduling strategies can be used for uncertainty and variability environments: (*i*) dynamic scheduling and (*ii*) predictive-reactive scheduling. Dynamic scheduling does not create or update production schedules. Instead, it uses decentralized production control methods to dispatch jobs when needed. On the other hand, predictive-reactive scheduling has two main steps. The first step generates a production schedule, and the second step updates the schedule in response to disruptions to minimise their impact on system performance. Thus, predictive-reactive scheduling is the most used strategy in practice as it allows the update of the schedule.

Additionally, for implementing predictive-reactive scheduling, there are three types of policies: periodic, event-driven, and hybrid (VIEIRA; HERRMANN; LIN, 2003). These policies aim to respond when an event has a sufficient impact that requires a new schedule (FERREIRINHA *et al.*, 2020). In periodic, schedules are generated at regular intervals, i.e., any disruptions between rescheduling periods are ignored until the next period, which can compromise the system's performance. In event-driven scheduling, it is rescheduled each time an event occurs, e.g., the arrival of new jobs. However, many events can occur in large manufacturing systems, and the system can be in a permanent state of rescheduling, resulting in low stability and excessive computational demands. Then, the hybrid policy reschedules the system periodically and also when some particular events happen, such as machine breakdowns, job arrivals, or job cancellations, among others. Implementing this hybrid policy can be advantageous, allowing the scheduling to be revised at the beginning of each period and when significant disruptions occur.

Considering the papers in the BP, 7 addressed the predictive-reactive strategy. The paper by Nouiri *et al*. (2019) proposed a generic multi-agent system (MAS) composed of a smart manufacturing multi-agent system and a smart energy provider multi-agent system. The architecture is based on interactions and negotiations between factory agents and energy providers to achieve a common goal: sustainability. The agent-based distributed model combines the predictive and reactive parts when solving the energy-aware scheduling and rescheduling problem. Paprocka (2019) developed an efficient tool for maintenance planning and production scheduling, divided into four modules: (*i*) a database to collect information about failure-free times, repair times of a machine, and failure modes; (*ii*) a prediction module of failure-free and repair times; (*iii*) a predictive scheduling and rescheduling module; and (*iv*) a module for evaluating the accuracy of a prediction and the efficiency of the maintenance team. The presented model achieves quality schedules, and the combination of the modules for maintenance planning and production scheduling constitutes a powerful tool for uncertainty prediction and dealing with unexpected failures. Andrade-Pineda *et al*. (2020) proposed a novel dual-resource constrained flexible job-shop problem (DRCFJSP) procedure to schedule repair orders and allocate workers at the different work centers in an automobile collision repair shop. The method addressed the predictive-reactive strategy, where the work contents, the route on the shop floor, or the required due date is subject to change. The reactive schedule is triggered by events like due date changes, arrival delays, changes in job processing time, and rush jobs. Basán *et al*. (2020) presented several scenarios from a real-life air separation industrial plant to show interesting trade-offs between the predictive and reactive-iterative strategies. The paper aims to provide a reactive-iterative MILP-based (mixed-integer linear programming) solution for solving the scheduling problem of a power-intensive process working under time-sensitive electricity prices.

The paper by Ferreirinha *et al*. (2020) proposed a prototype model connected to the MRP software of the company to schedule and reschedule through meta-heuristics. According to defined objectives, when interruption events occur, such as new order arrival or order cancellation, the tool starts rescheduling through a dynamic event module that combines dispatching rules that best fit the performance measures pre-classified by the Kano model. This approach showed good effectiveness, where the maximum tardiness was always less than zero, and the mean flow time was minimised whenever possible. Qiao *et al*. (2020) proposed a novel partial repair rescheduling solution that consists of a criterion and a scheduler. The criterion decides the segment of the original schedule to be repaired by detecting a match-up point (predictive step). The scheduler generates a new schedule segment to replace the original and impacted one with single machine-oriented or machine-group-oriented match-up rescheduling algorithms (reactive step). Finally, Paprocka, Krenczyk e Burduk (2021) developed a predictive-reactive method for joint scheduling of production and maintenance tasks. The method generates a basic schedule with the Ants Colony Optimization (ACO) application. A predictive schedule is built by planning the machine's technical inspection at the predicted failure-free time. Thus, flexible operations are allocated to the machine during an increased risk of failure.

This present study also addresses the predictive-reactive strategy for production scheduling due to its simple principle, ease of implementation, and widespread use in practice (ZHUANG *et al*., 2022). However, in contrast to the papers reviewed so far, the proposed approach seeks to integrate inventory data with production scheduling, generating a rescheduling to deal with material non-availability. Moreover, the hybrid policy is adopted, which combines periodic and event-driven policies. This combination is advantageous since not only a periodic schedule is implemented, but also rescheduling can be generated if disruptive events occur, requiring modifications to the initial schedule (AYTUG *et al*., 2005).

5.1.2.2 Inventory and production scheduling

Inventory management is fundamental in PPC. As one of the PPC activities, production scheduling is responsible for allocating resources to individual products and product batches, aiming to minimise inventory costs and set up costs while also considering the constraints involved (RAJAGOPALAN; SWAMINATHAN, 2001). Bose (2006) comments that excessive inventory ties down cash, as inventories such as finished goods, work-in-process, raw materials, spare parts, and others represent 80% or more of the working capital in some industries. However, the authors also state that material non-availability can lead to stock-outs, causing production disruption and service level failures. For companies to honour their commitment to supply finished goods on time and in the right quantity requested by the customer, PPC should regulate the quantity and volume of inventories, as well as define when and how many reorders to place (ANDWIYAN; IRSAN; MURAD, 2017). Thus, inventory management must be able to handle the trade-off of maintaining inventory levels neither too low nor too high.

Three basic planning steps are required for a manufacturing operation, regardless of the size or nature of the process (TOOMEY, 2012). The first step is determining a manufacturing plan, which will be based on anticipated or actual customer demand and the required inventory to meet that demand. The second step is to check the material and capacity requirements to meet the manufacturing plan. Then the third step is the purchase of the necessary material and the execution of the manufacturing plan. The execution of the manufacturing plan is typically based on recommended manufacturing orders, usually generated by a material requirement planning (MRP) system. Toomey (2012) also states that production scheduling is executed in the third step with the goal of completing manufacturing by the due date with minimum lead time and maximum machine utilization.

Accordingly, inventory availability is usually considered in long-term planning, which means that traditionally, there is little possibility of responding to shortages since the quantities shown are planned to be available, but not currently available (WILD, 2017). However, when production scheduling is being executed at the operational level, disruptions (events) can change the system status and affect performance. Vieira, Herrmann e Lin (2003) comment that if it causes significant deterioration in performance, the event should trigger rescheduling, or reactive scheduling, to reduce the impact on production execution. The authors also list a series of events that are considered the factors to trigger reactive scheduling, such as: machine breakdown, urgent job arrival, job cancellation, due date change, delay in the arrival or shortage of materials, and change in job priority, among others. Although many factors disrupt production execution, machine breakdown is the central and most explored problem in the literature (SOBASZEK; GOLA; KOZLOWSKI, 2020).

However, this scenario is changing. Machine breakdown continues as an important issue and should be further explored, but material non-availability is also attracting attention alongside this disruption event. As evidence, the result of the SLR presented 9 papers from PB that explored the integration of inventory with production scheduling with different approaches. Among these papers, only the paper by Basán *et al*. (2020) adopted the predictive-reactive strategy aiming to solve the scheduling problem of an energy-intensive process operating under time-sensitive electricity prices (see subsection 5.1.2.1). To deal with this problem, a new production schedule is generated daily in order to react to changes in electricity prices. In addition, this new schedule considers the current spot market price, operation mode, production rate, and plant inventory level.

In the remaining 8 papers, one adopted the dynamic scheduling strategy, and 7 did not define which scheduling strategy they approached, as defined in subsection 5.1.2.1. From these papers, 4 integrated the inventory level into the scheduling. Hubbs *et al*. (2020) proposed a deep reinforcement learning (DRL) method to address the uncertainties in the scheduling problem, adopting a dynamic strategy. The approach illustrated its application in an industrial, single-stage, and continuous chemical manufacturing process. When new orders arrive, a schedule can be generated almost instantly via a sequence of forward passes through a deep neural network. Results showed that the DRL method outperforms the naive MILP approaches and is competitive in terms of profitability, inventory levels, and customer service. Wu e Maravelias (2020) presented a general mixed-integer programming model for periodic production scheduling. The formulation is based on the state-task network (STN) representation. Every 26 hours, the model is run to generate an optimized schedule, which considers accurate inventory levels, policies, different demand patterns and profiles, and flexible assignment of tasks to units. Tirkeş, Çelebi e Güray (2021) developed a MILP for production planning and scheduling decisions. The model can be used for flexible production systems, especially for small companies that need to adapt to unforeseen variations in demand. In addition, an inventory-planning model is developed to check the level of inventory on a monthly basis for each product based on the scheduling scenario. The approach can cope with varying demands by offering a detailed costing procedure and implementing an effective inventory model. In the paper by Dong e Maravelias (2021), the authors proposed novel terminal inventory constraints, based on expected demand, for online production scheduling in different production environments. The method considered the relationship among inventory levels of different materials, thus overcoming a limitation of traditional threshold approaches, which constrain material inventory levels independently. As a result, the proposed constraints can effectively prevent stock-out and achieve substantial savings on inventory holding costs.

Besides this last paper that considered the inventory holding cost, other 3 papers also integrated this issue into the production scheduling. Izadi, Ahmadizar e Arkat (2020) proposed a new integrated production scheduling, vehicle routing, inventory, and outsourcing problem. To solve that, a hybrid algorithm incorporating a Genetic Algorithm with Dominance Properties (GADP) was proposed. Then, a schedule is generated for joint in-house production and distribution, considering the jobs that must be outsourced in order to minimise total production cost, inventory holding, outsourcing, and distribution. Duffuaa *et al*. (2020) developed a model for integrating production (production scheduling and inventory), maintenance planning, and quality control decisions for a single machine. The model determines the decision variables and optimizes the total cost per unit time resulting from production scheduling, inventory holding, maintenance, and process control. The study provided a viable approach for jointly optimizing production scheduling, maintenance, and quality, providing savings ranging from 2.62 to 6.78 percent. Hu *et al*. (2021) investigated an integrated inventory and production scheduling problem in a manufacturer that deals with perishable goods. The authors proposed a hybrid intelligent algorithm, called Imperialist Competition Algorithm-Variable Neighborhood Search (ICA-VNS), to find an optimal schedule to minimise the sum of inventory and production costs. The results showed that the hybrid algorithm outperformed compared to the standard ones.

Finally, the paper by Georgiadis *et al*. (2019) addressed the integration of inventory with reactive scheduling. The study implemented an optimization-based technique for the production scheduling problem of a large-scale yogurt production facility. An efficient solution strategy is proposed to consider rescheduling decisions through a reactive scheduling approach. The reactive scheduling successfully handled facing new information events, such as order modifications, new orders, and order cancellations. Moreover, for the generation of the optimized schedule, a scenario was tested where the actual production varies from the planned, i.e., a disruption in inventory is assumed, meaning that the previous day's production was not as expected. As a result, the model was successfully integrated with the company's enterprise resource planning (ERP) system, and an optimal weekly schedule was derived in a short computational time. Additionally, a significant reduction in total cost is achieved compared to the schedule realized by the industry.

Although these recent studies address inventory integration with production scheduling, to the best of our knowledge, no studies have addressed material non-availability as a disruptive event. Nevertheless, this event is one of the most important considerations in inventory problems, as this means that the production system faces a back-ordered shortage or lost sales (NOBIL; CÁRDENAS–BARRÓN; NOBIL, 2018). The raw material non-availability supply may arise from situations such as supplier difficulties, abrupt changes in demand, national or international financial crises, political conflicts between countries, among others (MIGALSKA; PAWLUS, 2020). Traditionally, to deal with this, it is recommended to maintain an extra amount of inventory, the buffer, in alignment with the MRP. However, many companies prefer to maintain minimal inventory, considering Just-In-Time (JIT) deliveries, allowing them to respond sensitively to changes in customer demand without high costs (KELLE; MILLER, 2001).

Thus, this paper addresses the integration of inventory data with production scheduling. More specifically, the raw material non-availability was considered a disruptive event during production execution, i.e., it is the trigger for reactive scheduling. Moreover, the raw material's non-availability is due to three factors: (*i*) delayed delivery by the supplier, (*ii*) lack of inventory accuracy, and (*iii*) excessive consumption caused by rework due to quality problems in production. Considering these factors, the impact of material non-availability is mitigated through real-time rescheduling, production continuity, and a targeted service level.

5.1.2.3 Production scheduling methods

Since the 1950s, mathematical programming formulations have been proposed to solve production scheduling problems. These formulations are optimization methods based on operations research, which aim to determine the best possible production plan considering the minimization of total costs or the maximization of total profit (DÍAZ-MADROÑERO; MULA; PEIDRO, 2014).

From the BP, it was possible to identify which approaches and techniques are still being implemented in the most recent studies. Chart 7 presents a summary and analysis of the reviewed papers. Díaz-Madroñero, Mula e Peidro (2014) state that typical mathematical programming approaches in production scheduling problems are linear programming, integer linear programming, and mixed integer linear programming (MILP). In fact, among the 19 papers reviewed, 8 still applied mathematical programming. For example, Faccio, Nedaei e Pilati (2019) described a new mathematical model to determine an optimal schedule considering machine performance and efficiencies under specific conditions, such as energy consumption (EC), maximum tardiness, and completion time. The model addressed various sequencing rules considering machines operating in dynamic job shops. As a result, the analysis of the optimal completion time has shown that among all rules studied, First Come First Served (FCFS), Earliest Due Date (EDD), and Shortest Processing Time (SPT) have resulted in the least completion time with a value of 20 seconds.

The remaining 11 papers explored different approaches and techniques, such as the paper by Sobaszek, Gola e Kozlowski (2020), which proposed a predictive job scheduling method for application in the job-shop environment under the machine failure constraint. For this, the authors used elements of Markov process theory and ARIMA (auto-regressive integrated moving average) to describe the machine failure parameters. The method generated high accuracy in the completion time of all jobs and increased schedule stability.

Although mathematical programming is widely addressed, its application for dynamic production systems is shown to be a complex task. Then, simulation models may prove to be a good alternative (DÍAZ-MADROÑERO; MULA; PEIDRO, 2014). Simulation can support companies to become more aware of the dynamics and efficiency of their processes in a production planning context (UHLMANN; ZANELLA; FRAZZON, 2022). Barbieri *et al.* (2021) proposed a methodology that integrates digital twin (DT) into a flow shop to implement reactive scheduling when machine breakdown events occur. The DT architecture provides virtualization and interface of all the actors allowing the generation of a virtual environment to identify possible issues that would occur in the physical implementation. Two techniques were used to support the decision-making in the evaluated scenario: Discrete Event Simulation (DES) for being computationally more efficient, allowing the quick test of different production sequences, and the Genetic Algorithm (GA) to identify an optimised production sequence that minimises makespan. Another study that addressed simulation is the paper by Frye *et al*. (2019). The authors presented a data-driven approach that applies Machine Learning (ML) models to generate production schedules adaptively. The goal of the approach is to reduce idle times and waste as quickly as possible when ML models identify any deviation from the expected process completion. DES was also used in this study, as it links the scheduling algorithm with the prediction results and analyses the efficiency of the anticipated rescheduling. As a result, the execution time of the cycle schedule can be reduced by approximately 10% compared to the case where adaptive ML-based scheduling was not applied.

As observed in these last two studies, DES was combined with other techniques. Díaz-Madroñero, Mula e Peidro (2014) comment that simulation does not guarantee optimal solutions. Thus, adopting hybrid models that combine simulation with mathematical programming models can be advantageous. Then, hybrid models, such as the simulation-based optimization (SBO) approach, stand out for combining the advantages of both simulation and optimization, besides allowing studies in dynamic and complex environments (BERGER;

FRAZZON; DANIELLI, 2018; LIN; CHEN, 2015). The SBO approach integrates optimization techniques into the simulation analysis and includes an objective function defined through the simulation model. Compared to mathematical programming techniques, which are usually based on very simplified system models, SBO allows modeling more complex systems (GOSAVI, 2015).

Besides the relevance of the SBO approach, other approaches are also receiving highlights with the advent of Industry 4.0, such as digital twins, artificial intelligence, or machine learning (COELHO *et al*., 2021). These approaches require a large amount of data for their implementation, and the shop floor is an environment with a large amount of data available during the manufacturing process (JI; WANG, 2017). Consequently, it becomes essential nowadays that manufacturing systems incorporate mechanisms with intelligent features to achieve optimal performance and reactivity, regardless of any scenario (JIMENEZ; GONZALEZ-NEIRA; ZAMBRANO-REY, 2018).

In summary, different methods have been developed to solve production scheduling problems. However, considering the advantages of the SBO approach and the promising results in the study by Takeda-Berger *et al*. (2022b), we extend here this preliminary study and validate the conceptual model proposed by Takeda-Berger *et al*. (2022a). Thus, seeking to contribute to advancing knowledge, we propose a new approach for production scheduling using machine learning and SBO.

Quadro 7 – Summary of BP

(continua)

Number	Authors	Type	Industry segment	Scheduling strategy	Enviroment	Triggers (events)	Method applied
1	Faccio, Nedaei e Pilati (2019)	Experimental data	Not Informed (NI)	Not Defined (ND)	Job-shop	Not Applicable (NA)	Mathematical
2	Frye *et al.* (2019)	Case study	Siemens Tecnomatix	ND	Job-shop	High overall lateness	Machine learning models Discrete event simulation (DES)
3	Nouiri *et al.* (2019)	Experimental data	NI	Predictive-Reactive	Flexible job-shop	Changes in energy consumption Machine breakdowns Urgent job arrival Changes in operations processing time	Particle Swarm Optimization
4	Georgiadis *et al.* (2019)	Case study (Practical)	Mevgal Ltd., Greece	ND	ND	Order size modifications New orders Orders cancellations	Mixed-Integer Linear Programming (MILP)
5	Paprocka (2019)	Experimental data	NI	Predictive-Reactive	Job-shop	Machine breakdown	Hybrid Multi-Objective Immune Algorithm (H-MOIA)
6	Hubbs *et al.* (2020)	Case study	Chemical Manufacturing Process	Dynamic scheduling	ND	New orders	Reinforcement Learning Algorithm
7	Wu e Maravelias (2020)	Experimental data	NI	ND	ND	Every 26 hours	MILP
8	Izadi, Ahmadizar e Arkat (2020)	Experimental data	NI	ND	ND	NA	Hybrid algorithm: Genetic Algorithm (GA) with Dominance Properties (GADP)
9	Qiao *et al.* (2020)	Experimental data	Minifab Model	Predictive-Reactive	ND	Machine breakdown	Single-Machine-oriented match-up Rescheduling (SMUR) Machine group-oriented match-up Rescheduling (GMUR) Right shift rescheduling (RSR)

Fonte: Elaborado pelos autores (2022).

Quadro 7 – Summary of BP

(conclusão)

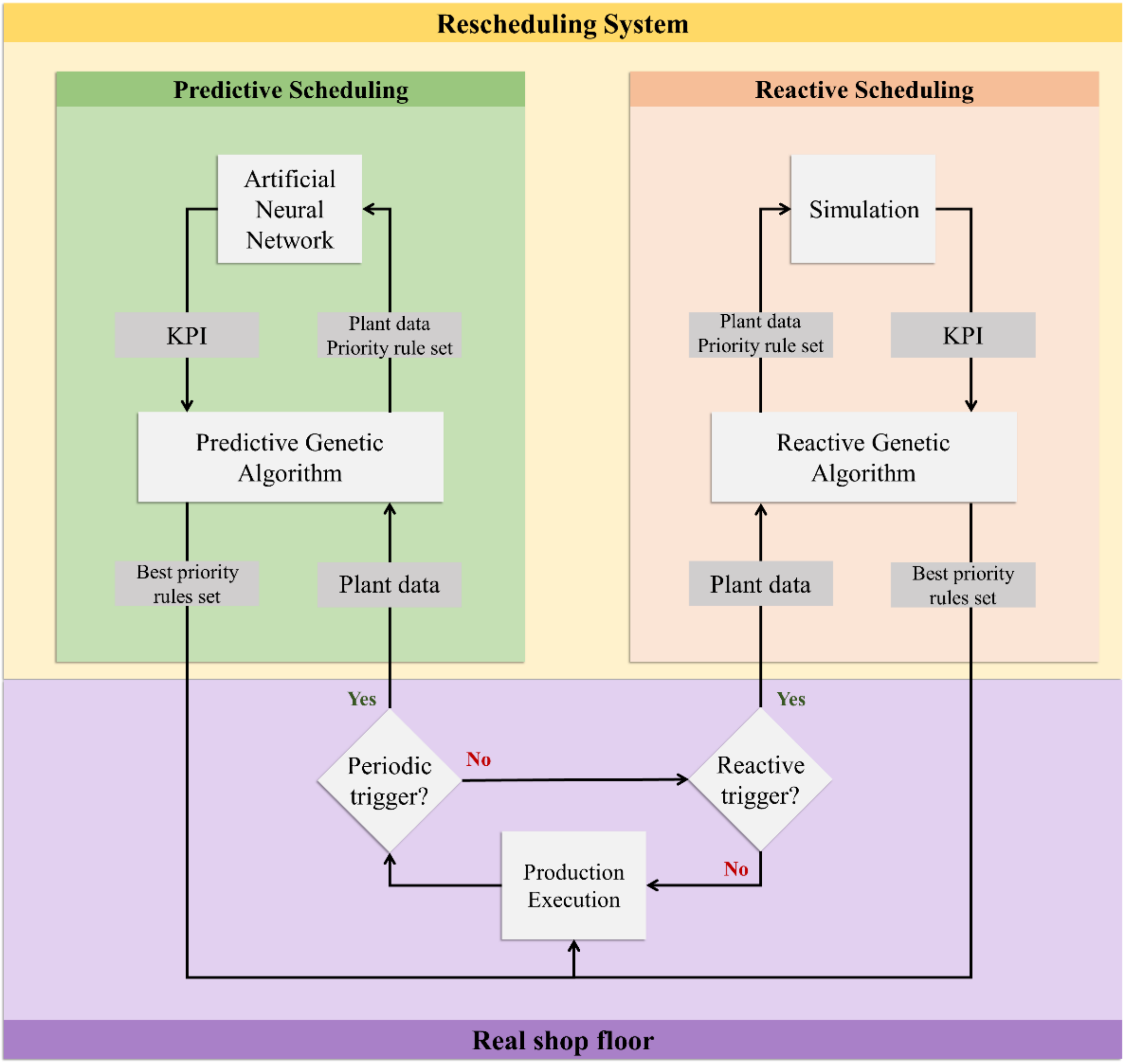
Number	**Authors**	**Type**	**Industry segment**	**Scheduling strategy**	**Enviroment**	**Triggers (events)**	**Method applied**
10	Basán *et al.* (2020)	Case study	Industrial Nitrogen Plant	Predictive-Reactive	ND	Changes in electricity prices	MILP
11	Duffuaa *et al.* (2020)	Experimental data	NI	ND	ND	NA	Mathematical
12	Ferreirinha *et al.* (2020)	Experimental data	NI	Predictive-Reactive	ND	New order arrival Order cancellation	Kano's Model Simulated Annealing (SA)
13	Sobaszek, Gola e Kozlowski (2020)	Experimental data	NI	ND	Job-shop	Machine breakdown	Markov Chains ARIMA (auto-regressive integrated moving average)
14	Andrade-Pineda *et al.* (2020)	Case study	Car Service Network	Predictive-Reactive	Flexible job-shop	Due date changes Delay in arrival Changes in job processing time Rush jobs	MILP
15	Barbieri *et al.* (2021)	Experimental data	NI	ND	Flow-shop	Machine breakdown	DES GA
16	Tirkeş, Çelebi e Güray (2021)	Case study	Tarihi Yudumla Syrup and Jam Production Company	ND	ND	NA	MILP
17	Hu *et al.* (2021)	Experimental data	Manufacturing with perishable raw materials	ND	ND	NA	Hybrid algorithm: ICA-VNS (Imperialist Competition Algorithm-Variable Neighborhood Search)
18	Dong e Maravelias (2021)	Experimental data	NI	ND	ND	NA	MILP
19	Paprocka, Krenczyk e Burduk (2021)	Experimental data	NI	Predictive-Reactive	Job-shop	Machine breakdown	Ant Colony Optimisation

Fonte: Elaborado pelos autores (2022).

5.1.3 An inventory data-driven approach for predictive-reactive production scheduling

The inventory data-driven approach for predictive-reactive production scheduling integrates real and virtual environments. It seeks to mitigate the impact of material non-availability in a complex stochastic manufacturing system. Figure 26 presents the proposed approach, which is an adaptation of the conceptual model by Takeda-Berger *et al*. (2022a). The approach comprises a two-step model that combines machine learning to generate predictive scheduling and simulation-based optimization to react to material non-availability and generate reactive scheduling. The following subsections describe how each step works.

Figura 26 – Proposed approach



Fonte: Elaborada pelos autores (2022).

5.1.3.1 Machine learning for predictive scheduling

Machine learning (ML) is known for its ability to handle many problems of NP-complete nature, which often appear in the production scheduling field (WUEST *et al*., 2016). In the last two decades, the application of ML techniques has received more visibility. This fact can be justified by introducing Industry 4.0 concepts and promoting the use of technologies in industrial environments. Thus, there was an increase in the availability of large amounts of complex data and, consequently, a need for usability and power of the available ML techniques (SMOLA; VISHWANATHAN, 2008).

Generally, ML techniques are classified according to three primary categories: (1) supervised learning, (2) unsupervised learning, and (3) reinforcement learning (MONOSTORI, 2003). In supervised learning, a dataset includes its desired outputs (or labels) to allow a function to compute an error (feedback) for a given prediction. Supervision occurs when a prediction is made, and an error is produced (actual vs. desired) to change the function and learn the mapping. In unsupervised learning, a dataset does not include a desired output; therefore, there is no way to supervise the function. Instead, the function tries to identify patterns and relationships among the data by classifying them into data sets with common features. In reinforcement learning, the algorithm tries to learn actions for a given set of states that lead to a goal state. Similar to supervised learning, feedback is provided only after receiving a reinforcement signal and not for every action taken.

There are different ML techniques available, each with advantages and disadvantages. The most common way to choose a technique is to evaluate the available data on the problem explored. Thus, supervised ML techniques in manufacturing systems are the most widely used mainly due to the nature of the problems, with a large amount of available data and mostly labeled data (WUEST *et al*., 2016). Also, it is important to mention that the different algorithms can be combined to maximize their advantages (BISHOP, 2006).

Considering this context, the first step of the proposed approach comprises the application of the ANN technique in combination with the GA to generate predictive scheduling. According to the study by Takeda-Berger *et al*. (2020), these two techniques have been widely applied and promising for dealing with production scheduling problems. Metaxiotis e Psarras (2003) define ANN as a technique based on the way biological nervous systems process information, i.e., it is the structure of the information processing system. The authors also comment that ANN is composed of many processing units interconnected in networks, the “neurons”; through a learning process called “training”, this system becomes capable of solving problems. Once the learning phase is completed, ANN can provide answers to the inputs in an online system that seeks optimizations, acting more quickly than traditional heuristics that often take hours, days, or weeks to provide desirable results (GOMES *et al*., 2016). Thus, the main advantages of ANN are their ability to self-organize, learn, and generate predictions quickly (NEMIROVSKY *et al*., 2018).

In the approach, predictive scheduling is called periodically, e.g., every period. Since it occurs more than reactive scheduling, it becomes relevant that it does not take too long to provide a solution. In addition, predictive scheduling considers data according to production planning, which means that the information is more stable. Thus, the details of the shop floor data are less relevant. Therefore, instead of using simulation to design the manufacturing system, ANN was used to obtain a faster periodic predictive scheduling (AKYOL; BAYHAN, 2007). Then, the ANN is trained to mimic the shop floor, using a set of input data (e.g., demand, inventory, priority rules, work-in-process metrics, etc.) and output data (e.g., a chosen KPI). Considering the manufacturing system represented through ANN, GA iteratively uses this scenario to test different combinations of priority rules, in order to find the best set of rules (according to the considered KPI) that will compose the predictive scheduling. A concept about GA will be presented in the next subsection. However, one of the justifications for its implementation is its iterative nature of providing a best-fit strategy and creating high-quality solutions reasonably (PATIL, 2008). Furthermore, since the late 1990s, hybrid systems have been developed to solve complex problems, and ANN with GA techniques are among them (WANG, 2019).

5.1.3.2 Simulation-based optimization for reactive scheduling

The second step comprises applying the SBO method, combining DES with GA to generate the reactive scheduling. De Sousa Junior *et al*. (2019) comments that SBO has received attention in recent research because it is a method capable of representing and improving discrete event systems. The author also defines that SBO evaluates a specific solution space to find the best configuration that will help to improve key performance indicators (e.g., service level, delivery times, average delay). As mentioned in previous sections, SBO integrates optimization techniques into simulation analysis, usually including an objective function implicitly defined through the simulation model (KLEIJNEN, 2015).

Here in this study, we combine the GA optimization technique to interact with the simulation. GA is a global search optimization technique that builds a population of solutions and combines them using operators such as mutation and crossover to develop a better population of solutions (SEXTON; SRIRAM; ETHERIDGE, 2003). This technique has been successfully applied to various problems, especially in manufacturing and scheduling, due to its ability to explore the search space globally and find good solutions quickly (ZHANG; WANG; ZHENG, 2006).

In the proposed approach, reactive scheduling is event-driven, i.e., when a disruption occurs during production execution. Since it is expected that these events are not very frequent, it was decided to adopt the SBO because the simulation allows for a more detailed representation of the shop floor. To accomplish this, the current state of the shop floor can be fed into the simulation using data such as inventory levels, work-in-process, current demand, machine availability, etc. Thus, the generation time for the reactive scheduling will be longer than the predictive scheduling, as it requires that each possible schedule be simulated to evaluate its performance. Then, every time an event occurs, GA is triggered to adapt the simulation model to the current state of the real system. Having triggered optimization, GA starts to reselect for each individual machine the priority rule, generating a population of possible solutions and using the simulation model to evaluate them. The simulation model simulates this set and returns the KPI of this executed simulation for optimization. This interaction between GA and simulation will occur until one of the stop criteria of GA is reached. Finally, as a result of this SBO method, there is a reactive schedule, which comprises the best set of priority rules found for the current shop floor state. Therefore, it is possible to continue the production execution mitigating the impact of material non-availability in the manufacturing system.

5.1.4 Application case

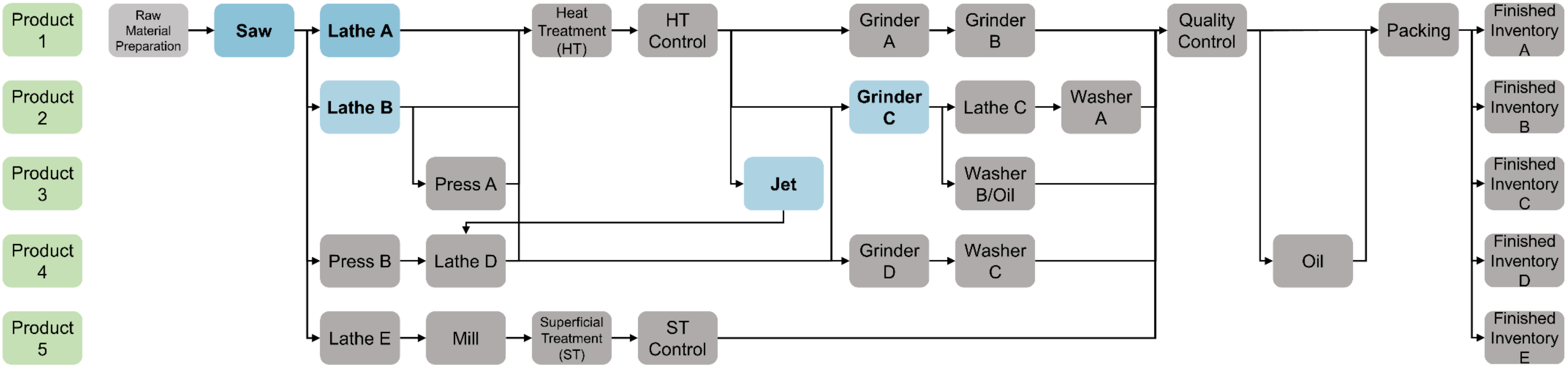
This section is structured as follows. First, the scenario is described. Secondly, it is described how the approach was implemented. Then, is presented the general parameters used in the experiment. Next, it is explained how the ANN was trained and its parameters used. Finally, is presented the parameters of the Gas implemented.

5.1.4.1 Case study

A case study was conducted to validate the proposed approach. The company in this case study is medium-sized, founded in 1968, and located in southern Brazil. The company operates in the metal-mechanic segment, and its main activities are: serial precision machining of bars, forgings, and castings; assembly of metal sets, and thermo-forming. Its market is focused on the production of metal parts in general, and it is one of the country's largest suppliers of parts to the automotive and agricultural sectors.

The scenario chosen for this study is a job shop environment, which handles several jobs with different processing orders of machines. Figure 27 shows the shop floor, with 25 processes and where 5 different products are processed. Although the company has a larger product portfolio, these five products were defined because they compete for the same resources, which is critical for the company's production schedule. Thus, these 5 processes (in bold in Figure X) are shared by the products: (1) Saw, (2) Lathe A, (3) Jet, (4) Grinder C, and (5) Lathe B. Then, different priority rules are determined for these 5 processes that are disputed by the products, while the others use First In First Out (FIFO) priority.

Figura 27 – Shop floor of the case study

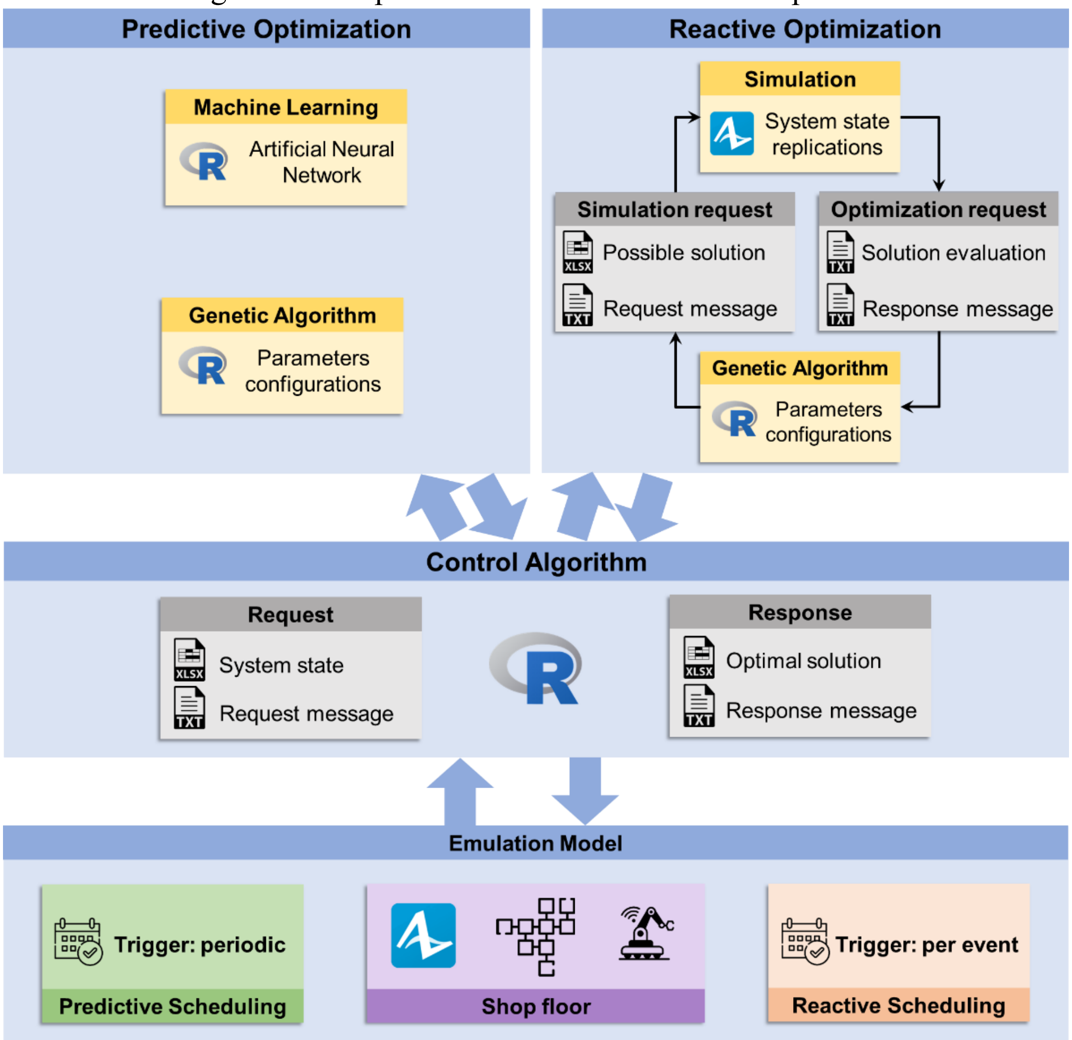


Fonte: Elaborada pelos autores (2022).

5.1.4.2 Implementation

For the implementation of the approach, two software were used. The Simulation and Emulation models were implemented in AnyLogic 8 Personal Learning Edition 8.5.2. using Discrete Event Simulation (DES). The open-source RStudio software designed to integrate the R 3.6.3 programming language (R CORE TEAM, 2013) was used for optimization. The GAs were then implemented using the GA package (SCRUCCA, 2013). The RStudio software was also used for the ANN, but the Tensorflow and Keras packages in R were adopted (ABADI *et al.*, 2016). The integration between both software was implemented with a Control Algorithm in R. Figure 28 shows the communication process of the approach, which works as follows.

Figura 28 – Implementation of communication process



Fonte: Elaborada pelos autores (2022).

An Emulation model in AnyLogic represents the real production system. The Control Algorithm mediates the interaction between the Emulation and the optimizations. For the optimization of the predictive scheduling, an algorithm in R with GA and ANN is used. For the optimization of the reactive scheduling, another GA algorithm in R is used along with a Simulation model in AnyLogic. This Simulation model is a copy of the Emulation model but is only used for the SBO method.

Periodically, every two weeks, predictive scheduling is triggered. At this time, the Emulation model pauses and captures the current state of the shop floor and saves the data in a .xlsx file. The Emulation sends a .txt message to the Control Algorithm that initializes the predictive GA. Next, the GA loads the data received in .xlsx, which will be used as input to the ANN. The GA then generates an initial population of individuals (set of priority rules) to be evaluated. Combined with the manufacturing data, GA uses the ANN to evaluate the fitness of each of these individuals, which is represented by the service level KPI. Several generations will evolve until one of the stopping criteria is reached, and an optimal solution is obtained. This solution is returned to the Control Algorithm, which writes the result to a .xlsx file. Finally, the Control Algorithm sends a .txt message to communicate to the Emulation that the optimization has been completed. The Emulation reads and applies the new priority rules and proceeds with a production execution.

During the production execution, if there is a material non-availability event, reactive scheduling is triggered, and the Emulation is paused again. The trigger happens when the raw material that is in shortage is delivered. Then, similar to predictive scheduling, the Emulation model captures the current state of the shop floor and saves the data in a .xlsx file. Next, the Emulation sends a .txt message to the Control Algorithm that initializes the reactive GA. The GA then generates an initial population of individuals (set of priority rules) to be evaluated and writes a solution to the .xlsx file. After that, the GA sends a .txt message to the Simulation model, which starts loading the current state of the shop floor and the first set of rules proposed by the GA. The Simulation runs for two weeks of operation and saves the service level KPI in a .txt file. Then, the Simulation sends a .txt message to GA confirming that it has finished the analysis. This interaction continues until the GA tests all the individuals of its initial population. The remainder of the dynamics follows equally as in the optimization of predictive scheduling.

Regarding the implemented triggers, these were defined as follows. The periodic trigger occurs every 2 weeks and is called immediately before a new production order is injected. On the other hand, the reactive trigger was implemented to be called when the events of raw material non-availability and machine breakdown occur. When the failure occurs, the reactive optimization immediately calls for the machine breakdown event. For the raw material non-availability event, it is called when the raw material in shortage arrives. This strategy triggers the optimization algorithm when the plant recovers the capacity to produce the affected product. Thus, the optimization can find a solution that mitigates the effects caused by the period when the material was unavailable. During this period of shortage, the production continues for the products that have raw material available. Therefore, as long as there is some raw material available, the machines will not be idle.

Additionally, whenever a reactive trigger is called, a two-week counter is started, during which no other predictive or reactive trigger can occur except for the machine breakdown trigger. This implementation avoids the solution found by reactive optimization being replaced by a subsequent optimization event and thus increases the efficiency of the overall optimization process.

5.1.4.2.1 Numerical experiments

The experiment was simulated for 12 months. The company operates in 3 shifts, 19.1 working hours per day, 6 days per week, and 4 weeks per month. The processing and set-up times were defined based on historical data and multiplied by a stochastic factor using a triangular distribution. The demands were defined based on 3-year historical data, also considering a 20% seasonality over the 12 months. This seasonality generates a demand peak for the manufacturing system, and it allows the evaluation of the behaviour of the approach under this increased demand scenario. The products are manufactured in batches, and the production schedule is planned on a weekly basis. The delivery of the finished products occurs through Milk Run logistics, i.e., the products are collected every 2 days.

Initially, the system is adjusted with a quantity of raw material to cover a one-month production, including a safety stock of 10%. Meanwhile, the inventory of the finished products follows the Just-in-time concept, which is adjusted to deliver the necessary quantity until the first product batches are produced. Thus, the inventory quantities can vary from 2 days to 2 weeks, according to the lead time of each product. The machine breakdown was implemented deterministically, as the company could not provide the breakdown data for individual machines. In order to increase the number of disruption events to the system, each of the 5 shared processes is set to fail every 9 weeks, one at a time, and the breakdown lasts for one day. When a machine breakdown occurs, a reactive optimization is also triggered.

Considering that the approach aims to integrate the inventory data with the production scheduling, specifically in this study, it tested the potential of the approach to react to the raw material non-availability. Then, as mentioned before, raw material non-availability can occur due to three factors. The values considered for these factors were adjusted according to the data of the company: (*i*) the raw material is delivered every 2 weeks, and a delay by the supplier of 30% can happen, (*ii*) the inventory accuracy is 99%, and (*iii*) there is a 5% chance of having quality problems in the products in process, during each control inspection (HT control, ST control and Quality control).

As also defined in this study, production scheduling is composed of priority rules. Although many different rules have been studied in the literature (PINEDO, 2016), we considered the promising results in the studies of Frazzon, Kück e Freitag (2018), Agostino *et al*. (2020), and Takeda-Berger *et al*. (2022b) to determine which priority rules would be adopted. Thus, the following priority rules were used: Earliest Due Date (EDD), Modified Due Date (MDD), Operational Due Date (ODD), Shortest Processing Time (SPT), and Least Global Slack (SLK). Chart 8 presents an explanatory summary of the rules.

Quadro 8 – Priority rules definitions

Priority Rule	Definition
EDD (Earliest Due Date)	Jobs with the earliest due date are prioritized.
SPT (Shortest Processing Time)	Jobs with the shortest processing time are prioritized.
SLK (Least Global Slack)	Jobs with the smallest time margin to finish are prioritized.
MDD (Modified Due Date)	Jobs are prioritized by either the earliest due date or the earliest finish date.
ODD (Operational Due Date)	Due dates are assigned for each step of the process (operation), and jobs with earliest operation due date are prioritized.

Fonte: Elaborado pelos autores (2022).

Finally, to evaluate the operational performance of the proposed approach, the KPI of Service Level (SL) was implemented, as it is an important indicator for the company and a relevant indicator for the manufacturing system. The SL is updated at each collection of finished products, is evaluated individually for each product, and calculated according to Equation 2.

$$SL_i = 1 - \frac{DP_i}{TD_i} \tag{2}$$

The TD represents the accumulated demand for product i in question, and the DP represents the amount of these products *i* delivered late. In order to calculate the average SL, it was used the geometric mean between the SL of each product *i*, according to Equation 3, where n is the total number of products.

$$SL = \sqrt[n]{SL_1 \times SL_2 \times \ldots \times SL_n} \tag{3}$$

The geometric mean was chosen because it penalizes the discrepancies between the values evaluated in a more accentuated manner. For example, if the SL of one of the products is close to zero, the geometric mean result will also tend to zero. Thus, optimizing the average SL can guarantee that all products will have acceptable SL levels in a scenario where all products have the same priority level for the company.

Considering this KPI, the performance of the approach was compared with five benchmark scenarios that use a static set with the same priority rule for each machine. One of these scenarios, the EDD rule, is the company's current strategy.

5.1.4.2.2 A supervised machine learning: artificial neural network

The overall process of supervised ML consists of several steps for handling and setting up the training and test data set. Considering the problem investigated, the necessary data is identified, and if needed, the data can be pre-processed. Generally, the process for training the ML technique is as follows, according to Wuest *et al*. (2016). Initially, the technique is trained using the training data set. Then, the trained technique is evaluated using the data set to analyse its ability to perform the targeted task. Depending on the performance of the trained technique with this evaluation data set, the parameters can be adjusted to optimize the performance in case the performance is already good. However, if the performance is unsatisfactory, the process has to be started again at an earlier stage, depending on the actual performance.

Considering the implementation of predictive scheduling, a forecast horizon of 2 weeks was first defined. As it was considered stochasticity in the processing time, raw material delivery time, and product quality rate, the model presents a high variability, and a forecast with a longer time will lose accuracy. This time was defined empirically for this case study. Thus, an analysis will be necessary to define this forecast horizon to generate the predictive scheduling since each model can present behaviour with different dynamics. Next, the ANN training was conducted, divided into 5 stages: (*i*) definition of the output; (*ii*) definition of the inputs; (*iii*) generation of a data set with combinations of inputs and their respective outputs; (*iv*) definition of ANN training parameters and (*v*) ANN training.

Thus, in stage (*i*), the output was defined as the Service Level KPI. The inputs were defined in the next stage (*ii*), which should significantly influence the determined output variable. Considering this condition, the following inputs variables were defined: 1) the quantity of raw material inventory for each product; 2) the demand for the next 2 weeks for each product; 3) the quantity of finished product inventory for each product; 4) the priority rules in each shared machine; 5) the quantity of work-in-process for each product; 6) the number of products in the queues of each shared machine; and 7) the service level at the beginning of the period. In total, 31 inputs affect the output result, which is the SL after 2 weeks of plant operation.

In stage (*iii*), to generate the training data set with combinations of inputs and their respective outputs, the Emulation model in AnyLogic was used, which was configured to register the shop floor state (input variables) periodically. The Emulation runs for 12 months, and the input and output data are recorded every 2 weeks (defined forecast horizon). The Emulation is run several times with different combinations of priority rules, in order to create a diverse data set that represents the operation of the shop floor under study. The generation of this data set is important because when the GA uses the ANN to conduct the optimization iterations, the GA will test different priority rules to improve the performance of the KPI. Thus, it is necessary to generate the shop floor behaviour data using different combinations of rules to obtain a well-trained ANN. Through this dynamic with Emulation, it was possible to generate a data set with over 70,000 input and output data. In a real scenario, even if the company has the historical data of its manufacturing system, it is unlikely to have the data of the plant operating with different priority rules. Therefore, it is necessary to generate this data through the Emulation model.

For stage (*iv*), the ANN training parameters were defined empirically after several tests. The ANN has a three-layer structure. Each layer has 51, 25, and 15 neurons, with an output layer representing the SL. The layers use a “relu” (Rectified Linear Unit activation function) activation function. The optimization technique used was ‘rmsprop’ (RMSProp optimizer) using the Mean Absolute Error metric. A total of 200 training epochs were defined with a 15% validation split. The ANN configurations can be found in the available Keras Package document (KERAS, 2022).

Finally, in stage (*v*), the ANN training is conducted. Then, considering the parameters previously defined in (*iv*) and the over 70,000 data sets generated in stage (*iii*), 95% of this data was used to train the ANN, and 5% was allocated to verify the ANN accuracy after its training. This configuration made obtaining an ANN trained with 98.5% accuracy possible. After the ANN is trained, its weights are saved in a file, and the ANN can be loaded during its use in predictive optimization without the need for retraining. However, it is important to note that the quality of the ANN is directly dependent on the data used to train it. Thus, the training remains valid as long as the data represents the system’s current state. In case of changes in the plant, such as process modifications, product modifications, and priority rule options to be considered, among others, a new data generation and subsequent training will be necessary.

5.1.4.2.3 Genetic algorithm for optimization

Genetic algorithms are general search techniques based on natural selection and genetics and have been successfully applied to various optimization problems (LIAW, 2000). Pinedo (2016) describes how GA works when applied to scheduling. Accordingly, GA generates sequences or schedules as individuals (chromosomes) or members of a population, and its fitness characterizes each individual. An individual’s fitness is measured by the associated value of the objective function. The procedure works iteratively, and each iteration is called a generation. The population of one generation consists of survivors from the previous generation plus the new schemes, i.e., the offspring (children) of the previous generation. The population size usually remains constant from one generation to the next. The offspring are generated through reproduction and mutation of individuals that were part of the previous generation (the parents).

A mutation in a parent chromosome can be equivalent to an interchange of adjacent pairs in the corresponding sequence. In each generation, the fittest individuals reproduce while the less fit ones die. The processes of birth, death, and reproduction that determine the composition of the next generation can be complex and usually depend on the fitness levels of the individuals in the current generation. Through the mechanism called a crossover operator, a new schedule can be generated by combining parts of different schedules from the current population. Thus, the GA evolutionary process will be repeated until a pre-specified termination condition is satisfied.

In this sense, for both the implementation of predictive and reactive optimization, GA was used to generate a population of a set of priority rules to be tested to obtain the optimal solution. For that, the parameters of the GAs were defined empirically through experiments, as presented in Table 3. Mitchell (1998) comments that there are no conclusive results about the best parameters to adopt in GA. The influence of each parameter on the algorithm's performance depends on the complexity of the problem being addressed. Thus, determining an optimal set of values for these parameters will depend on conducting many experiments and tests.

Tabela 3 – GAs parameters

Parameters	GA for predictive scheduling	GA for reactive scheduling
Population	50	50
Crossover probability	0.8	0.8
Mutation probability	0.7	0.7
Maximum number of iterations	25	25
Maximum fitness	1	1
Maximum number of iterations without improvement	10	5

Fonte: Elaborada pelos autores (2022).

According to Table 3, it is relevant to comment that the termination condition referring to the "Maximum number of iterations without improvement" for the SBO method is lower because the population analysis is slower, as it depends on the Simulation to be tested. Therefore, it was decided to use a shorter termination condition to reduce the optimization time.

5.1.5 Results and discussion

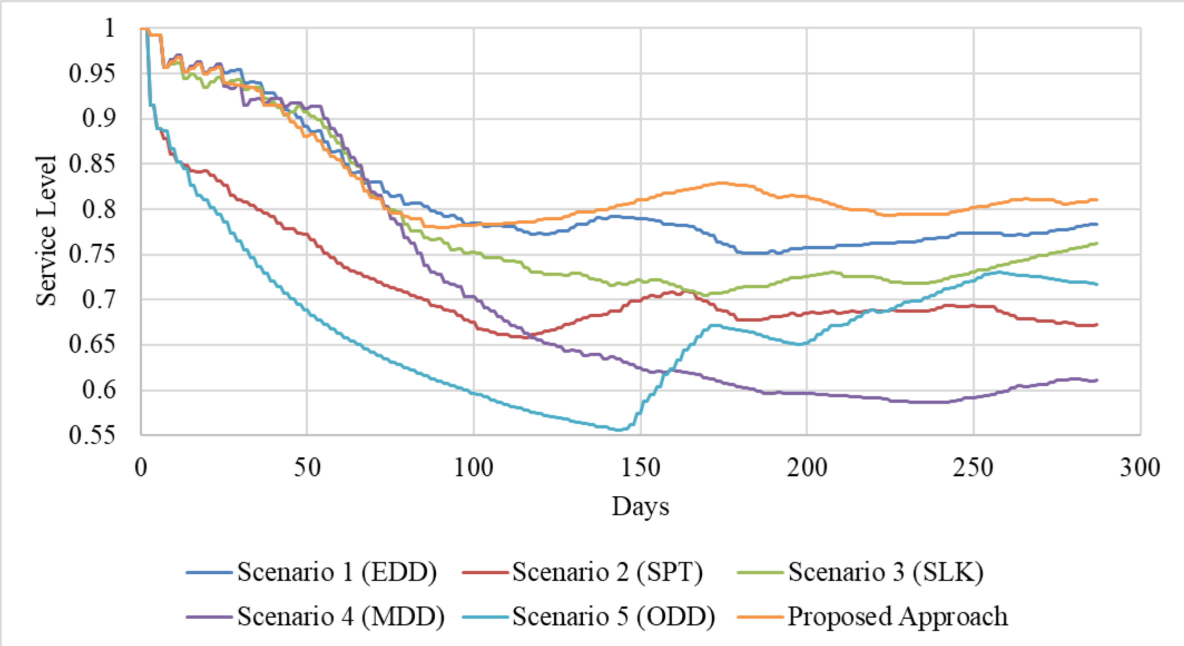
This section presents the case study results to validate the inventory data-driven predictive-reactive production scheduling approach, which combines machine learning to generate predictive scheduling, and simulation-based optimization to react to raw material non-availability and generate reactive scheduling.

The proposed approach was implemented to optimize the Service Level (SL) in terms of products delivered without delay, which is the significant KPI for the company in this study. It is important to point out that SL considers the products delivered on time, regardless of whether they were produced late. This means that even if a product was produced after its due date, the SL considers whether or not this product is available on the day of the collection of the finished product. This may occur because, with finished goods inventory, the product could be available to be delivered. Although this KPI was considered in this study, it is possible to use another different optimization KPI since the approach provides flexibility to changes.

To compare the operational performance of the approach, five scenarios were established, which used production schedules with fixed priority rules. In other words, in these scenarios, the priority rules are not amenable to change, keeping the same rules for all machines throughout the simulation. The scenarios defined are: Scenario 1 (EDD rule), Scenario 2 (SPT rule), Scenario 3 (SLK rule), Scenario 4 (MDD rule), and Scenario 5 (ODD rule). In addition, as mentioned in the previous section, the current strategy adopted by the company studied is the EDD fixed rule, represented by Scenario 1.

Initially, the scenarios were simulated using a fixed random seed. Figure 29 presents the evolution of the SL for each scenario during one year of simulation.

Figura 29 – Service Levels throughout the year comparison



Fonte: Elaborada pelos autores (2022).

According to Figure 29, the selection of the priority rules has a great impact on the SL. Different rules generate different configurations in response to the conditions on the shop floor over the simulation. The proposed approach obtained the best efficiency throughout the year for the evaluated seed, performing a higher SL for almost the entire period. Also, considering the simulation with a fixed random seed, Table 4 presents the SL result at the end of a year and the comparison with the strategy used by the company, Scenario 1.

Tabela 4 – Results comparison with fixed random seed

	Scenario 1 (EDD)	Scenario 2 (SPT)	Scenario 3 (SLK)	Scenario 4 (MDD)	Scenario 5 (ODD)	Proposed Approach
Service Level (SL)	78.3%	67.3%	76.2%	61.1%	71.7%	81.1%
% of deliveries delayed in relation to the EDD rule	-	+51%	+10%	+79%	+30%	-13%

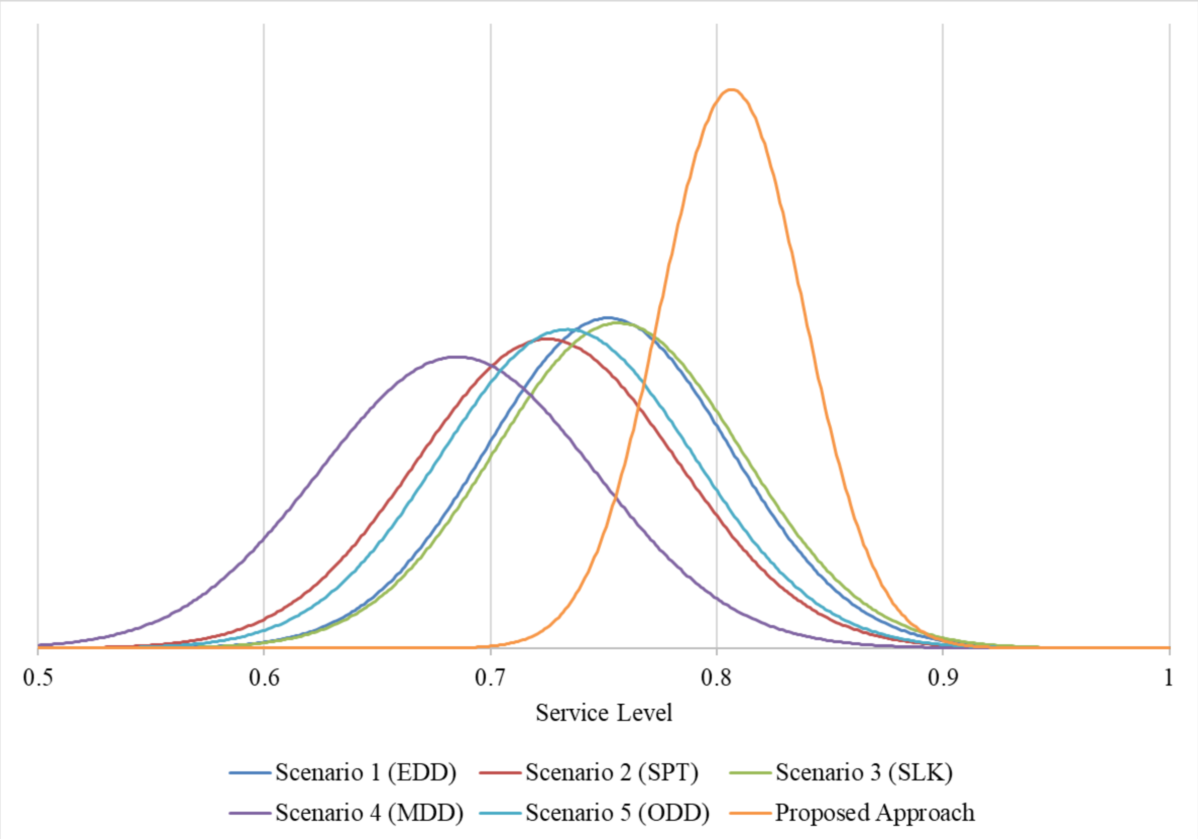
Fonte: Elaborada pelos autores (2022).

Evaluating the results in Table 4, the proposed approach reached an SL of 81.1%, while the best-fixed rule, EDD, delivered 78.3%. This strategy adopted by the company, Scenario 1, achieved the best result among the fixed rules evaluated. However, compared with this Scenario, the approach proposed in this study obtained better results, as it was able to reduce by 13% the average value of delayed deliveries to the client.

Nevertheless, due to the presence of stochasticity in the model, specifically in the processing times and in the rate of product quality, the evaluation of the scenarios with the same fixed random seed does not guarantee that the conditions will be exactly the same among the scenarios, affecting the fairness of the comparison. Thus, it becomes necessary to run several simulations with random seeds in order to obtain an average value for the results and thereby generate a fairer comparison.

Then, for the scenarios with a fixed rule, 1000 simulations were run with random seeds for each scenario. For the proposed approach, 25 simulations were run with random seeds. The reduced quantity of simulation runs for the proposed approach is justified by the presence of the implemented methods, as the optimizations demand more execution time. Accordingly, the final results presented a normal distribution; the curves are shown in Figure 30. The distribution for each scenario can be found in Appendix 1.

Figura 30 – Service level results distribution curves



Fonte: Elaborada pelos autores (2022).

Again, it can be seen in Figure 30 the impact that the different priority rules have on SL. Nevertheless, the variation width observed in the fixed rule scenarios is approximately constant among them. This fact shows that in scenarios where no intelligence is applied, the variation of the result is directly dependent on the variation of the system.

Moreover, it is noted that the proposed approach obtained a significant increase in the SL average value while the variation was reduced. This variation reduction can be attributed to the adopted methods, as they can adapt the system to a better operational performance even when facing system variations. Table 5 summarizes the final results, presenting the number of simulations run, the mean SL, the standard deviation, and the confidence interval.

Tabela 5 – Average results comparison

	Scenario 1 (EDD)	Scenario 2 (SPT)	Scenario 3 (SLK)	Scenario 4 (MDD)	Scenario 5 (ODD)	Proposed Approach
Number of simulations	1000	1000	1000	1000	1000	25
Mean SL	75.2%	72.5%	75.6%	68.5%	73.4%	80.7%
Standard deviation	5.4%	5.8%	5.5%	6.1%	5.6%	3.2%
99% Confidence interval	0.4%	0.5%	0.4%	0.5%	0.5%	1.6%
% of deliveries delayed in relation to the EDD rule	-	11%	-2%	27%	7%	-22%

Fonte: Elaborada pelos autores (2022).

From Table 5 it can be seen that the two fixed-rule Scenarios which obtained the best mean SL values were Scenarios 3 and 1, performing respectively 75.6% ±0.2% and 75.2% ±0.2%, considering a 99% confidence interval. These results show that, on average, the two scenarios have equivalent performance, which was impossible to identify in the previews simulations with a fixed random seed, given its limitations.

The proposed approach obtained a mean of 80.7% ±0.8%, considering a 99% confidence interval. The wider confidence interval can be explained by the reduced number of samples, which were limited due to the time required for each simulation. Nonetheless, it is evident that the proposed approach was statistically able to obtain a mean result superior to the fixed rule scenarios to that it was compared to. Furthermore, the proposed approach was able to reduce the average value of delayed deliveries to the client by 22% compared to Scenario 1.

Another aspect that is also important to discuss is regarding simulation times. A complete 12-month simulation with fixed rules takes about 1 second to run. But implementing the optimizations for predictive and reactive scheduling, this time increases significantly. An experiment performed in this case study, considering only the SBO method to generate both predictive and reactive schedules, took around 4 to 5 hours. On the other hand, an experiment considering the proposed approach, implementing ANN for predictive scheduling and SBO for reactive scheduling, took around 1.5 to 2 hours. This difference in time occurs due to the speed gain provided by the ANN. A single optimization run using the SBO method took 20 to 30 minutes to obtain an optimal solution, while ANN was able to obtain an optimal solution in 4 to 6 minutes.

However, the ANN is an approximate representation of the shop floor under study, designed based on the inputs and outputs defined and the data used for its training. Therefore, its response will not be as accurate as the SBO method, which uses a simulation model closer to the real environment capturing better the existing dynamics. Even though, it can be noted that the speed gain compensates for the accuracy loss. In this case study, the ANN delivered a solution 5 times faster.

Also, it is important to comment that 5 priority rules were considered for a total of 5 shared processes, which represents a total of 3125 (5^5) possible combinations of solutions. Since this quantity is relatively small, the GAs combined with each method did not require much time to obtain a solution close to the optimal one. Nevertheless, in different applications with more complex scenarios (e.g., a larger number of rules or processes), the quantity of possible solutions increases exponentially, resulting in a proportionally longer optimization runtime.

Given this consideration, using a technique capable of delivering results faster, such as ANN, becomes more attractive. The difference in performance between the methods validates the choice of ANN for predictive scheduling, as it occurs more frequently and thus will provide solutions in a faster time. It also validates the choice of the SBO method for reactive scheduling since the environment with disruptions demands a more complete analysis capable of considering the current data to obtain an optimized solution.

In summary, the results presented and discussed here prove that even in a dynamic and stochastic environment, with machine breakdowns, quality problems, raw material delays, and accuracy problems, the proposed approach showed to be efficient in mitigating the effects of these issues.

Since production scheduling is an important activity, as it represents the connection between planning and production on the shop floor, the proposed approach presented through the predictive-reactive strategy an efficient scheduling, contributing to the success of modern manufacturing systems. Furthermore, since scheduling influences and is influenced directly by inventory, the proposed approach, based on inventory data, is attractive to decision-makers. By using the approach, it is possible to obtain optimal solutions to mitigate the delay of jobs that have not been produced due to raw material non-availability and achieve an improved SL. This result has a positive impact on the manufacturing system, as it maintains productivity and efficiency in the face of disruptions, and on the clients, as it mitigates delivery delays.

Finally, especially nowadays, when manufacturing systems are encouraged to adopt approaches that integrate real and digital systems, data-driven decision-making becomes crucial to transform these systems. From this, the approach proposed in this study can significantly contribute to improving the operational performance of production scheduling and supporting digital transformation in production systems.

5.1.6 Theoretical and practical contributions

Manufacturing systems are becoming increasingly dependent on digital methods, and a wide variety of data-driven approaches are being experimented with to transform the resolution of classical manufacturing problems. In this context, the proposed approach aims to contribute by expanding the field of scientific knowledge on this topic but also by overlapping with industrial practice.

In theoretical terms, the systematic literature review contributed to confirming the research gap and guided the development of this research. Although the literature evidence on production scheduling is extensive, few studies have focused on integrating inventory data with production scheduling, especially considering the predictive-reactive strategy. Thus, the literature review has provided a general background about the relations between the contexts addressed. Moreover, another theoretical contribution is the presentation of an approach that covers the context of Industry 4.0, adopting supportive technologies for this scenario. Considering the incentive for a digital shop floor, the approach adopted the SBO and a machine learning technique, both methods considered application tendencies in these environments. Additionally, to the best of our knowledge, no other model in the literature has presented a joint approach combining simulation-based optimization and machine learning for predictive-reactive production scheduling based on inventory data.

In practical terms, firstly, it can be highlighted the contribution of this research with a feasible approach to be implemented in the structure of the production planning and control of the company. The approach presented promising results for the operational performance of the manufacturing systems, besides being of easy application and understanding, allowing it to be adapted and applied in different industrial segments. Second, corroborating with digital advances in manufacturing environments, data-driven approaches provide more efficient resource allocation. In this sense, the proposed approach contributes to predictive-reactive scheduling driven by inventory data, optimally sequencing the jobs to be processed, considering the available resources in real-time. The data-driven approach allows for better coordination of processes and technologies, providing a more integrated system and, here, impacting the service level positively.

Third, the case study conducted in a medium-sized Brazilian company contributes to promoting the digital transformation coming from the fourth industrial revolution in these environments. Although the concepts of Industry 4.0 have been explored for a decade, in developing countries, this aspect is still in an evolution process, and the development of scientific research can support the progress of its implementation. Finally, both practical and theoretical contributions of this research have a great positive impact on the industrial environment, improving understanding of the problems inherent in material non-availability, reducing information uncertainty, and providing knowledge about shop floor data. This knowledge allows decision makers to adapt schedules by mitigating, for example, the delay in fulfilling orders. In addition, it allows decision-making to be faster and smarter, presenting solutions that improve the operational efficiency of the manufacturing system, promoting competitiveness for companies.

5.1.7 Conclusion

During the last decade, manufacturing processes have been transformed into autonomous and adaptive production environments, allowing production monitoring, process optimization, diagnostics, and quality prediction, all in real-time through cyber-physical systems. Production scheduling is considered a complex task due to optimizing different competing objectives and reacting to unpredictable events, which may occur during processing. However, as it is an essential activity for production planning and control, it becomes necessary that new approaches are studied to progress production scheduling also in the context of Industry 4.0.

Thus, this paper presented an inventory data-driven predictive-reactive production scheduling approach, which corroborates with the evolving concepts of the fourth industrial revolution. In this approach, a machine learning technique, ANN, was combined with GA to generate the predictive scheduling. The simulation-based optimization method was also used to generate the reactive scheduling. The approach's main goal is to generate the best set of priority rules comprising the predictive and reactive schedules.

Considering the dynamic and uncertain nature of manufacturing systems, the developed approach is inventory data-driven, i.e., it considers inventory levels and other information from the current state of the shop floor. Accordingly, it is possible to feed the model with real-time data to generate both predictive scheduling periodically and reactive scheduling that deals with the events of material non-availability. The proposed approach was validated through a case study using computer simulation. The results showed that for the service level KPI, the approach is able to find a better solution than the compared scenarios. Therefore, even in a dynamic and stochastic scenario, with machine breakdowns, quality problems, raw material delays, and accuracy issues, the approach proved efficient in mitigating these variations' effects.

Two significant contributions emerge. First, it was shown that integrating inventory data with production scheduling is of utmost importance to the manufacturing environment, as it allows scheduling to allocate tasks effectively according to available resources. Second, this study's results advance the knowledge about new approaches to solving production scheduling problems that go beyond classical mathematical models, which are usually limited to the complexity required. The proposed approach has been shown to mitigate the disruptions in the manufacturing process and improve the overall service level.

Finally, some limitations and potential directions for future research can be highlighted. First, the approach was validated in a company from the metal-mechanic segment, and its results cannot be generalized to other segments. Thus, applying the approach to companies from other sectors is suggested to generate a comparison with the results obtained here. Second, five priority rules were selected to compose the production schedule. Several rules are found in the literature and studies proposing adaptations to the traditionally applied rules. However, it was decided to use standardized rules consolidated in the literature, and those considered the most commonly applied in industrial contexts. Thus, the inclusion and application of other rules in future research are suggested, allowing a new analysis of the results of the proposed approach. Third, the machine breakdown event was implemented in a deterministic way. Future research can include stochasticity in machine breakdowns, being a more realistic consideration, as well as encompassing other types of disruptive events, such as new order arrivals and order cancellations, among others. Furthermore, future studies can incorporate cost analysis into the proposed approach, providing an advantage in decision-making since the financial gains related to reducing delivery delays for clients would be evident.

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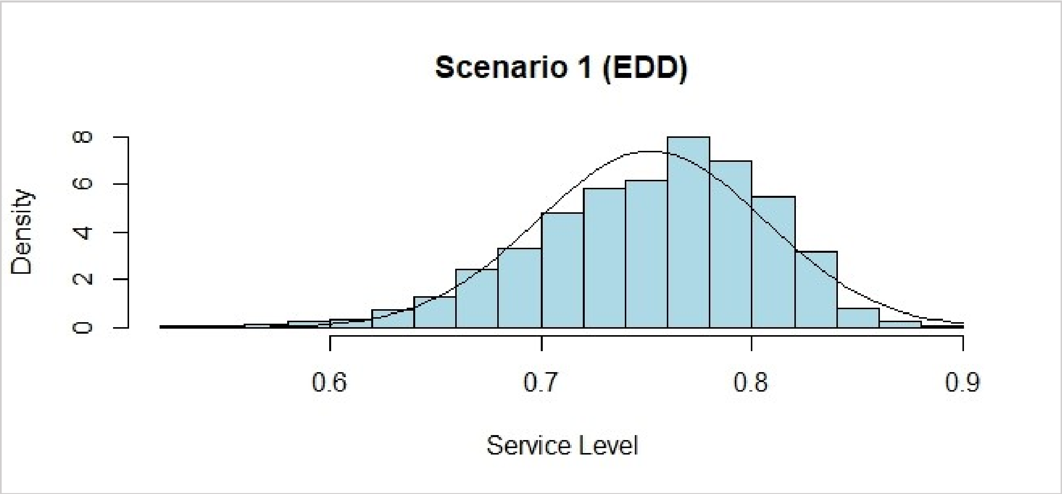
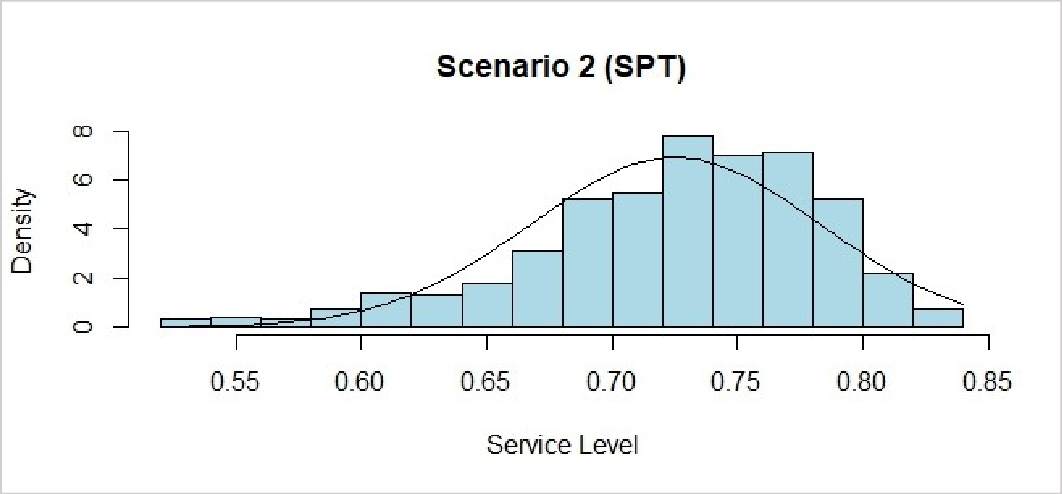
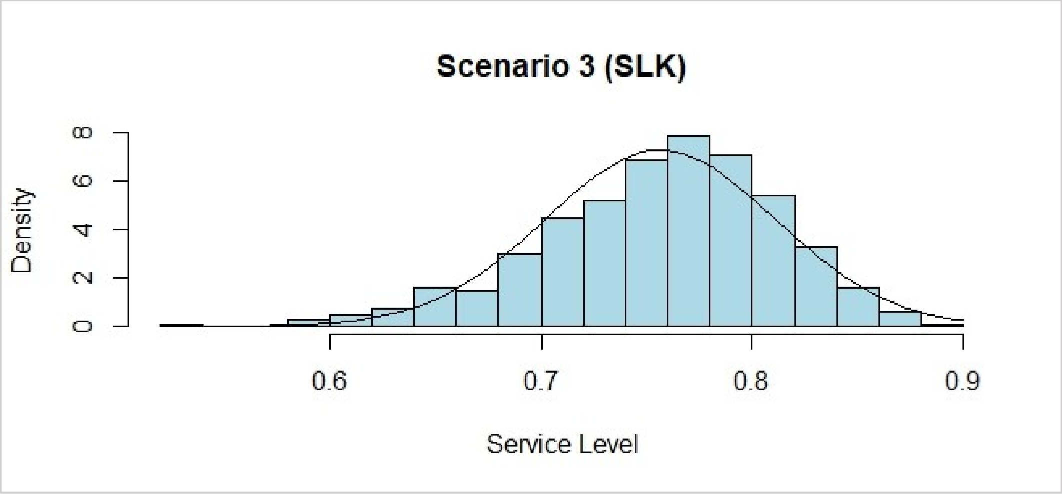
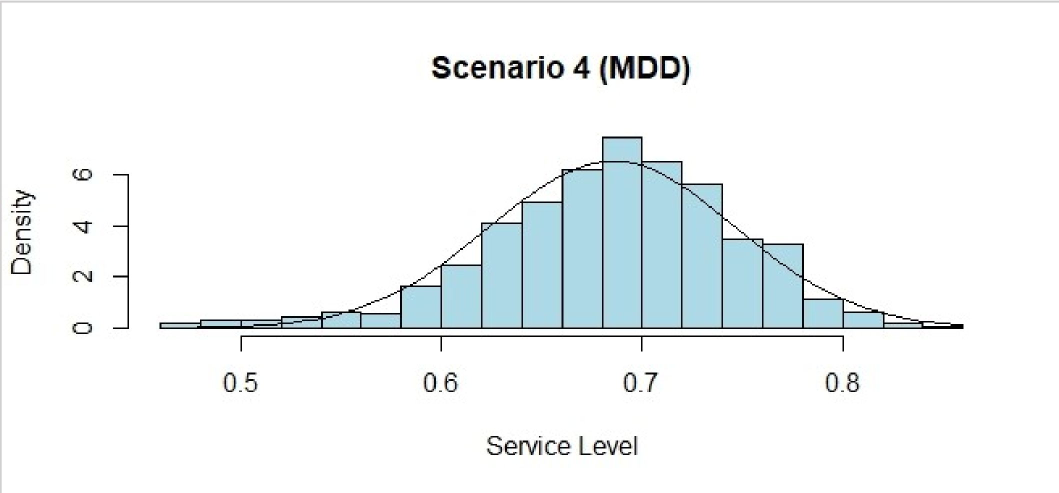
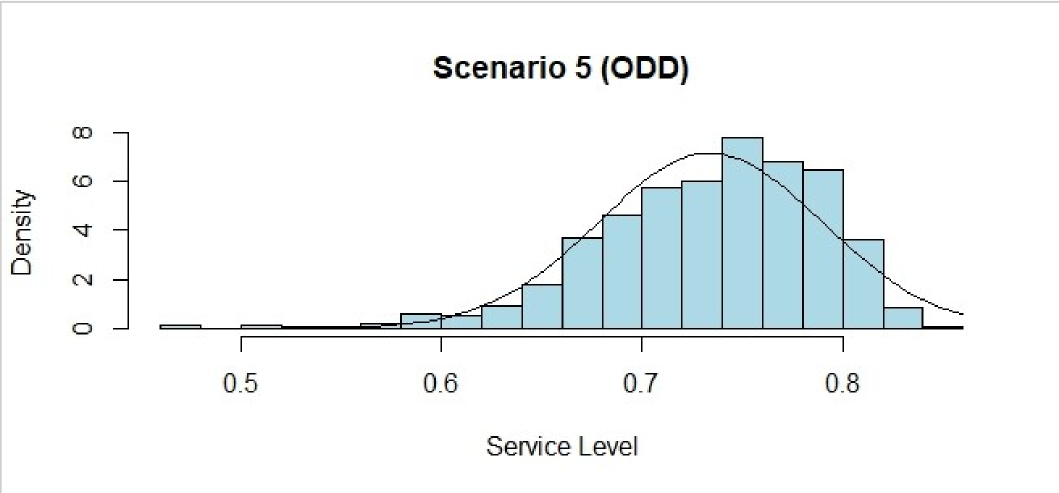
5.1.9 Appendix A – Scenarios distributions








Scenario 4 (MDD)
Density
0
2
4
6
0.5
0.6
0.7
0.8
Service Level


Scenario 5 (ODD)
Density
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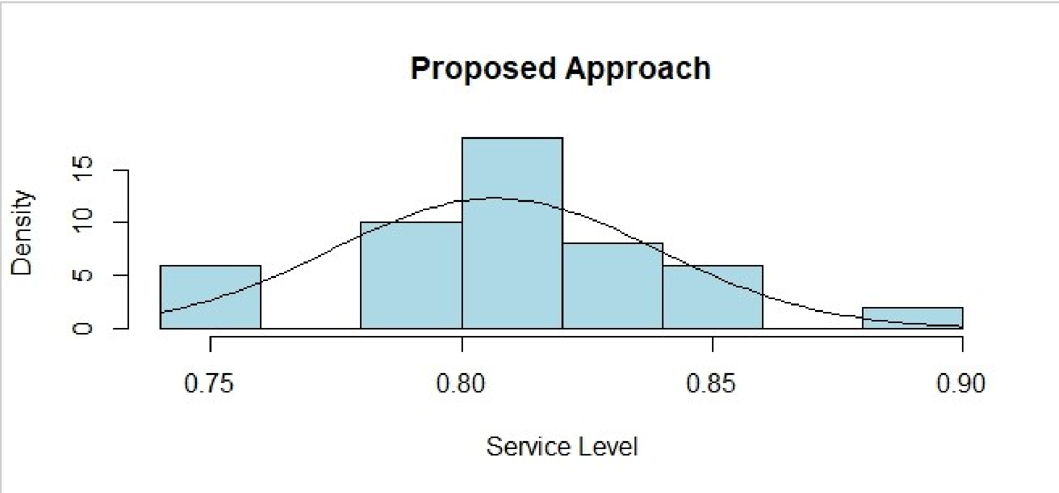
4
6
8
0.5
0.6
0.7
0.8
Service Level


Proposed Approach
Density
0
5
10
15
0.75
0.80
0.85
0.90
Service Level

CAPÍTULO 6
6 DISCUSSÃO/SÍNTESE DA TESE

Este capítulo busca sintetizar todas as etapas e os resultados desta pesquisa e destacar os achados mais relevantes para discuti-los em conjunto. Assim, o desenvolvimento dos Capítulos 3, 4 e 5 está alinhado para atingir o objetivo principal dessa tese que é proposição de um modelo de programação da produção preditiva-reativa orientada a dados de estoque provenientes do chão de fábrica.

No Capítulo 3, inicialmente um modelo conceitual preliminar foi desenvolvido, direcionando o sentido dessa pesquisa e fornecendo suporte para a construção da versão final do modelo conceitual. Em seguida, uma Revisão Sistemática da Literatura (RSL) foi conduzida, com o intuito de identificar quais são as principais técnicas de ML atualmente implementadas para abordar problemas de programação da produção. Entre os 31 artigos analisados, os resultados mostraram que o número de publicações tem crescido constantemente desde 2015, indicando um grande interesse na aplicação de técnicas de ML para a programação de produção. Além disso, a ANN destacou-se como a técnica mais implementada nas pesquisas, considerando este portfólio de artigos. Assim, esta RSL embasou a escolha da técnica de ML, a ANN, para ser adotada na programação preditiva do modelo conceitual proposto.

Ainda no Capítulo 3, uma nova RSL foi também conduzida sobre a integração dos dados de estoque com a estratégia da programação da produção preditiva-reativa. A finalidade dessa RSL é identificar as lacunas e oportunidades de pesquisas e apresentar um modelo conceitual final. A RSL foi conduzida através da técnica ProKnow-C, almejando responder três questões de pesquisas: (*i*) *quais estudos adotaram a estratégia da programação da produção preditiva-reativa?*; (*ii*) *quais estudos abordaram sobre a programação da produção baseada em estoque?* e (*iii*) *como as estratégias da programação da produção têm sido aplicadas?*. Para responder essas questões, foi selecionado um portfólio bibliográfico (PB) de artigos sobre o tema abordado. A obtenção desse PB seguiu alguns critérios como: palavras-chaves, área de estudo, tipo de documento, idioma, parâmetros de exclusão, entre outros. A partir disso, 55 artigos compuseram o PB e foram explorados por meio das análises bibliométrica e sistêmica. Ao observar a evolução da publicação dos artigos, notou-se que a partir de 2010 teve-se um aumento de estudos sobre a estratégia preditiva-reativa para a programação da produção. Além disso, em 2018 houve um aumento significativo na quantidade de publicações no mesmo ano, quando comparado com os anos anteriores. Tal fato, evidencia o interesse da comunidade acadêmica sobre o assunto, demonstrando a sua relevância e atualidade.

Para responder a primeira questão de pesquisa, os 55 artigos do PB foram classificados por categoria de acordo com seu conteúdo, ou seja, artigos que adotaram a estratégia preditiva-reativa, somente a estratégia preditiva, somente a estratégia reativa, nenhuma estratégica específica mencionada ou artigos de revisão. Como resultado, apenas 17 estudos buscaram resolver problemas de programação da produção adotando a estratégia preditiva-reativa. Embora o tema relacionado à programação da produção seja amplamente abordado na literatura, apenas 31% do PB adotaram a estratégia preditiva-reativa, indicando que ainda há espaço para explorá-la em pesquisas futuras.

Outro resultado da RSL, que responde a segunda questão de pesquisa, apontou que poucos trabalhos consideraram a integração dos dados de estoque com a programação da produção. Dentre os artigos do PB, 8 estudos definiram o estoque como uma variável de restrição para a programação da produção, porém nenhum adotou uma estratégia para reagir à indisponibilidade de material. Outros 3 artigos abordaram a estratégia preditiva-reativa e a disponibilidade de material, entretanto as suas proposições não estão inseridas no atual contexto da Indústria 4.0, já que o artigo mais recente foi publicado há treze anos. Assim, considerando o contexto dinâmico dos sistemas de manufatura, com chegadas e/ou cancelamentos de tarefas, quebras de máquinas, falta de matéria-prima, problemas de qualidade, entre outros, torna-se essencial novas abordagens de programação para lidar com essas incertezas e mitigar os seus impactos nos sistemas produtivos.

A terceira e última questão de pesquisa, buscou identificar quais métodos já foram implementados para resolver problemas de programação da produção. Dentre os artigos do PB, os resultados mostraram uma diversidade de métodos, porém predominantemente o uso da modelagem matemática. No entanto, a programação matemática nem sempre consegue lidar com os sistemas de produção, que em sua maioria são complexos e dinâmicos. Então, estudos que abordaram a Simulação de Eventos Discretos (DES) conseguiram incorporar mais complexidade e fornecer resultados promissores para a programação da produção. Além disso, constatou-se também que alguns estudos começaram a explorar técnicas de aprendizado de máquina (ML). Com o advento da Indústria 4.0, os ambientes do chão de fábrica têm sido modernizados e adequados para sustentar novas tecnologias. As técnicas de ML auxiliam a transformação da grande quantidade de dados disponíveis na manufatura, em informações competitivas para as empresas. Dessa forma, o uso dessas técnicas traz um novo olhar para uma otimização orientada a dados, possibilitando avanços nas tomadas de decisões sob incerteza.

Com a extensa análise da literatura conduzida, os resultados mostraram que ainda são poucos os estudos que abordaram sobre a integração dos dados de estoque com a estratégia de programação da produção preditiva-reativa. Considerando ainda o contexto da Indústria 4.0, tem-se o potencial de explorar novas abordagens para melhorar o desempenho operacional dos sistemas de manufatura. Então, constatada a lacuna e oportunidade de pesquisa, um modelo conceitual foi proposto estruturando uma abordagem para a programação da produção preditiva-reativa orientada por dados de estoque. Neste modelo, a combinação de uma técnica de ML, a Rede Neural Artificial (ANN), com o Algoritmo Genético (GA), fornece periodicamente uma programação preditiva considerando um melhor cenário para a manufatura, de acordo com um Indicador Chave de Desempenho (KPI) estabelecido. Entretanto, com a dinâmica do mundo real, a indisponibilidade do material causa interrupções na produção, o que aciona a abordagem da Otimização Baseada em Simulação (SBO), combinando o DES com o GA, para lidar com esses eventos. Assim, o SBO fornece uma programação reativa que é um conjunto otimizado de regras de prioridade para sequenciar os trabalhos em cada máquina considerando o estado atual do chão de fábrica. Este modelo conceitual proposto é genérico, podendo ser adaptado a outros cenários industriais e reagir perante diferentes eventos. Porém, especificamente nesta tese, a indisponibilidade de material foi considerada como o evento desafiador para os sistemas de manufatura.

No Capítulo 4, um caso teste foi apresentado a fim de validar parte do modelo conceitual proposto, ou seja, a programação reativa utilizando o SBO. A abordagem foi avaliada em um ambiente de produção *job-shop* utilizando dados de uma empresa fabricante de componentes mecânicos, situada no sul do Brasil. Este cenário foi implementado no *software* Anylogic 8® e o experimento considerou um ambiente estocástico, incluindo variações nos tempos de processamento, *setup* e estoque. Já a otimização foi implementada em linguagem R utilizando o pacote GA. Então, a fim de analisar a dinâmica da programação reativa baseada na disponibilidade de estoque, dois gatilhos acontecem para chamar o SBO: por período, ocorrendo todo início de mês e por evento, a cada três meses quando chega um novo lote de matéria-prima (MP). Dessa forma, toda vez que há a necessidade da reprogramar a produção, o GA é acionado para adaptar o modelo de simulação ao estado atual do sistema real. Com a otimização iniciada, o GA começa a selecionar novamente para cada máquina individual a regra de prioridade, gerando uma população de soluções possíveis e usa um segundo modelo de simulação (cópia do modelo principal) para avaliá-las. Este segundo modelo simula este conjunto de regras e retorna o KPI desta simulação executada para a otimização. Essa interação entre GA e a simulação ocorrerá até que um dos critérios de parada do GA seja atingido. Por fim, como resultado desse método do SBO, há a geração da programação reativa, que compreende o melhor conjunto de regras de prioridade encontrado para o estado atual do chão de fábrica.

Como o evento disruptivo considerado neste estudo foi a chegada de material, ou seja, uma diferença do nível de estoque de MP entre o sistema real e a simulação, uma lógica de controle de estoque foi desenvolvida a fim de controlar o material durante o processo. Nesta lógica, é verificado se inicialmente há MP disponível para começar a produção. Caso não haja, os trabalhos ficam aguardando a chegada da MP e enquanto isso, são classificados de acordo com as suas datas de entrega, para garantir a prioridade de consumo com a chegada do material. Assim que a MP chega, a otimização é acionada para fornecer uma nova regra de prioridade as máquinas e então, os trabalhos que estavam aguardando seguem para serem processados.

Neste caso teste as regras de prioridades utilizadas para compor a programação da produção foram: (1) *Earliest Due Date* (EDD); (2) *Modified Due Date* (MDD); (3) *Operational Due Date* (ODD); (4) *Shortest Processing Time* (SPT); e (5) *Least Global Slack* (SLK). Ao final do experimento, o desempenho da abordagem proposta é avaliado por meio do KPI de número de trabalhos atrasados (*Tardy Jobs*), ou seja, se a conclusão da produção de um trabalho for após a sua data de entrega, ele será contabilizado como atrasado. Esse KPI foi comparado com cinco cenários de referência os quais usavam uma programação estática, considerando somente a mesma regra de prioridade para cada máquina. Além disso, comparou-se com a atual estratégia da empresa, a qual também adota uma programação fixa, seguindo a regra *First In First Out* (FIFO).

Os resultados alcançados com essa primeira validação de parte do modelo conceitual proposto foram promissores. A abordagem da programação reativa utilizando o SBO apresentou os melhores resultados gerais, pois superou em média todos os outros cenários contrapostos. Comparando com a estratégia atual da empresa, a abordagem atingiu um desempenho significativamente superior, ou seja 30% melhor, o que representa uma quantidade menor do número de trabalhos atrasados. Além disso, a abordagem também operou melhor contra as programações com regras de prioridade fixas, mantendo a quantidade de trabalhos atrasados inferior. Assim, foi possível constatar que a adoção do SBO para a programação reativa é capaz de lidar com eventos estocásticos, como a indisponibilidade de material em tempo real, mitigando a quantidade de trabalhos atrasados.

Neste capítulo, também foi apresentado um *framework* para ilustrar a possível integração da abordagem proposta à arquitetura de tecnologia da informação (TI) em uma empresa. A estrutura compreende quatro sistemas principais: o sistema de planejamento de recursos empresariais (ERP), o sistema de execução da fabricação (MES), o sistema de aquisição de dados de produção (PDA) e o sistema de aquisição de dados de máquina (MDA).

Na dinâmica apresentada no *framework*, o sistema ERP gerencia o planejamento dos trabalhos que são as ordens de produção, planos de turnos, as rotas dos produtos, etc. O PDA é responsável pela coleta de dados sobre os processos no chão de fábrica, reunindo informações como o estado atual das operações planejadas, dados de processamento dos trabalhos e dados do estado da máquina (recebidos pelo MDA). O MES, considerado o sistema central nessa estrutura, recebe as atualizações contínuas dos dados dos sistemas ERP e PDA, armazenando-as e fornecendo-as como *input* para a abordagem proposta. O MES também é responsável pela execução da programação reativa, acionando a abordagem SBO periodicamente e por evento. Portanto, o MES seria o sistema principal para realizar a *interface* entre a abordagem proposta e o chão de fábrica, além de aplicar o resultado obtido, ou seja, as regras de prioridade nas máquinas para executar o sequenciamento dos trabalhos no chão de fábrica.

No Capítulo 5, o desenvolvimento da proposta final da tese é concluído e validado. Inicialmente, foi realizada uma atualização da RSL similarmente a revisão conduzida no Capítulo 3, a fim de identificar estudos recentes na área. Dessa forma, adotando os mesmos critérios de busca, o novo PB constou com 19 artigos para serem analisados. Como resultado desta RSL, pode-se destacar três aspectos. Primeiro, a quantidade de estudos abordando a estratégia da programação preditiva-reativa, conforme já apresentada na revisão do Capítulo 3, continuou em alta. Considerando o curto período de busca dos artigos entre os anos de 2019 e 2021, quase metade dos 19 artigos do PB abordaram essa estratégia. Esse resultado demonstra um contínuo interesse sobre o uso desta prática para lidar com problemas de programação da produção. Como segundo aspecto, constatou-se novamente que a quebra de máquina continuou sendo um dos eventos mais explorados dentre os artigos. Até o presente momento, não se identificou estudos que tenham abordado a programação preditiva-reativa baseada em dados de estoques, o que mantem a originalidade desta tese. O último aspecto é com relação aos métodos que foram recentemente aplicados para resolver problemas de programação da produção, constatando que a programação matemática continuou amplamente sendo adotada. Essa ocorrência pode ser justificada, pelo fato de a programação matemática possuir uma trajetória de sucesso, a qual contribui com pesquisas para essa área desde a década de 1950. Entretanto, também ficou evidente o surgimento de mais estudos adotando o método da DES, o qual permite incorporar mais complexidade ao modelo, além de estudos que exploraram técnicas de ML. Esses resultados demonstram que, dentro dessa temática da programação da produção, as abordagens que diferem da programação matemática ainda são emergentes, incitando oportunidades de pesquisa.

Em sequência à atualização da RSL, um estudo de caso foi conduzido para validar a proposição final do modelo proposto, baseada no modelo conceitual apresentado no Capítulo 3. A empresa estudada é de médio porte, atua no segmento metal-mecânico e está localizada no sul do Brasil. O cenário escolhido possui um chão de fábrica com um ambiente de produção *job-shop*, que lida com diversos trabalhos seguindo diferentes ordens de processamento de máquinas. Para a implementação do modelo, igualmente no Capítulo 4, foram utilizados dois *softwares*, porém algumas adaptações foram introduzidas para a geração da programação preditiva. O sistema de produção real é representado por um modelo de Emulação em Anylogic 8®. A interação entre a Emulação e as otimizações é mediada por um Algoritmo de Controle desenvolvido na linguagem R. Para a otimização da programação preditiva foi utilizado um algoritmo em R com GA e ANN. Para a otimização da programação reativa outro algoritmo GA em R é usado juntamente com um modelo de Simulação em Anylogic 8®. Este modelo de Simulação é uma cópia do modelo de Emulação, mas é usado apenas para a abordagem SBO.

Então, o modelo proposto consiste na seguinte dinâmica. A programação preditiva é chamada periodicamente, a cada duas semanas. Previamente, a ANN já foi treinada para imitar o chão de fábrica, usando um conjunto de dados de entrada (por exemplo, demanda, estoque, regras de prioridade, etc.) e dados de saída (por exemplo, um KPI escolhido). Considerando o sistema de manufatura representado através da ANN, o GA utiliza este cenário iterativamente para testar diferentes combinações de regras de prioridade, a fim de encontrar o melhor conjunto de regras (de acordo com o KPI considerado) que irá compor a programação preditiva. A execução da produção é iniciada seguindo o que foi estabelecido na programação preditiva. No entanto, ao longo do tempo, eventos de ruptura podem ocorrer e com isso, a programação reativa é acionada. Este acionamento foi implementado para ser chamado quando ocorrerem os eventos de indisponibilidade de matéria-prima e quebra de máquina. Para o evento de quebra de máquina, quando a falha ocorre, a otimização reativa é chamada imediatamente. Para o evento de indisponibilidade de matéria-prima, esta é chamada quando chega a matéria-prima que estava em falta. Esta estratégia permite que o algoritmo de otimização seja acionado quando a fábrica recupera a capacidade de produzir o produto afetado e assim, a otimização tem a possibilidade de encontrar uma solução que atenue os efeitos causados pelo período em que o material não estava disponível. É importante comentar que, a indisponibilidade de matéria-prima pode ocorrer devido a três fatores: (*i*) atraso na entrega do material pelo fornecedor, (*ii*) falta de acuracidade no estoque e (*iii*) consumo excessivo de material causado por retrabalhos devido a problemas de qualidade na produção. Ademais, o funcionamento da programação reativa ocorre igualmente a dinâmica apresentada no Capítulo 4.

Neste estudo de caso as regras de prioridades utilizadas para compor a programação da produção também foram as mesmas adotadas no caso teste. Entretanto, o desempenho do modelo final proposto é avaliado por meio do KPI de Nível de Serviço (*Service Level*, SL). Este diferente KPI foi escolhido por ser um indicador importante para a empresa em estudo e também por ser um indicador relevante para os sistemas produtivos. Assim, considerando este KPI, o desempenho do modelo foi comparado com cinco cenários de referência que utilizam um conjunto estático com a mesma regra de prioridade para cada máquina e um destes cenários, que é a regra EDD, é a estratégia atual da empresa.

Os resultados finais obtidos pela simulação computacional mostraram que, os dois cenários de regras fixas que obtiveram os melhores valores médios de SL foram os cenários com as regras SLK e EDD, com um desempenho respectivamente de 75,6% $\pm$0,2% e 75,2% $\pm$0,2%, considerando um intervalo de confiança de 99%. Já o modelo proposto obteve uma média de 80,7% $\pm$0,8% de SL, considerando um intervalo de confiança de 99%. Por meio desses resultados ficou evidente que, estatisticamente o modelo proposto foi capaz de obter um resultado médio superior ao dos cenários de regras fixas com os quais foi comparado, superando também a atual estratégia da empresa. Assim, constata-se que mesmo em um ambiente dinâmico e estocástico, com quebras de máquinas, problemas de qualidade, atraso de matéria-prima e falta de acuracidade no estoque, o modelo proposto mostrou ser eficiente em mitigar os efeitos destes problemas.

Adicionalmente, outro aspecto importante para ser discutido é com relação aos tempos de simulação. Um experimento realizado neste estudo de caso, considerando apenas o método

SBO para gerar tanto a programação preditiva quanto a reativa, levou cerca de 4 a 5 horas. Por outro lado, um experimento considerando o modelo proposto, implementando a ANN para a programação preditiva e o SBO para a programação reativa, levou cerca de 1,5 a 2 horas. Esta diferença no tempo ocorre devido ao ganho de velocidade proporcionado pela ANN. Uma única execução de otimização utilizando o método SBO levou cerca de 20 a 30 minutos para obter uma solução ótima, enquanto a ANN foi capaz de obter uma solução ótima em torno de 4 a 6 minutos. Entretanto, a ANN é uma representação aproximada do chão de fábrica, projetada com base nas entradas e saídas definidas e nos dados utilizados para o seu treinamento. Portanto, a sua resposta não será tão precisa quanto a do método SBO, que utiliza um modelo de simulação mais próximo do ambiente real, capturando melhor a dinâmica existente. Mesmo assim, pode-se notar que a perda de precisão é compensada pelo ganho de velocidade. Neste estudo de caso, a ANN forneceu uma solução 5 vezes mais rápida.

Então, considerando este fato, o uso de uma técnica capaz de fornecer resultados mais rapidamente, como a ANN, torna-se mais atraente. Dessa forma, a diferença de desempenho entre os métodos valida a escolha da ANN para a programação preditiva, pois ela ocorre com mais frequência e, portanto, fornecerá soluções em um tempo mais rápido. Ao mesmo tempo, também valida a escolha do método SBO para a programação reativa, já que um ambiente com interrupções exige uma análise mais completa, capaz de considerar os dados atuais para obter uma solução otimizada.

6.1 CONTRIBUIÇÕES TEÓRICAS E PRÁTICAS

As três fases dessa tese, descritas nos Capítulos 3, 4 e 5, apresentaram de forma individual resultados parciais que se complementam quando integrados para o alcance do objetivo geral. Então, a partir dos resultados encontrados, o presente trabalho traz diferentes contribuições teóricas e práticas.

Embora as evidências da literatura sobre a programação da produção sejam extensas, uma quantidade significativamente menor de estudos levou em consideração a integração dos dados de estoque com a programação da produção, especialmente considerando a estratégia preditiva-reativa. Assim, em termos teóricos, a revisão sistemática da literatura contribuiu para identificar a lacuna de pesquisa e direcionar o desenvolvimento dessa tese, corroborando para aumentar o campo científico sobre o tema e também proporcionando uma compreensão geral quanto os contextos abordados. Cabe destacar ainda que, esta Fase revisou mais de quatro décadas de pesquisas relacionadas ao tema. Sendo que, mais de mil artigos foram identificados e destes 55 utilizados na análise da pesquisa, selecionados por meio de uma técnica sistemática consolidada, aumentando a validade e confiabilidade dos resultados.

Adicionalmente, a classificação dos métodos praticados na resolução dos problemas de programação da produção, forneceu uma visão do que já foi largamente explorado e dos métodos promissores frente ao novo contexto dos sistemas de manufatura. Com isso, outra contribuição teórica é a apresentação de um modelo conceitual abrangendo o contexto da Indústria 4.0, adotando métodos favoráveis para este cenário. O modelo conceitual apresenta uma abordagem para integrar os dados de estoque com a programação preditiva-reativa e lidar com a indisponibilidade de material. Considerando o fomento para um chão de fábrica digitalizado, o modelo adotou o SBO e uma técnica de *machine learning*, ambos métodos apontados como tendência de aplicação nesses ambientes.

Muitas vezes os objetivos de uma pesquisa acadêmica não se sobrepõem com a prática industrial. No entanto, pode-se destacar que essa tese contribui em termos práticos pois busca beneficiar a programação da produção através de um modelo factível para a estrutura do planejamento e controle da produção da empresa. No mundo real, onde o ambiente da máquina é mais complexo, é extremamente difícil resolver esse tipo de tarefa usando modelos matemáticos, já que pode haver muitas suposições que não são consideradas nos modelos teóricos. Dessa forma, o uso da simulação se torna uma ferramenta poderosa devido a sua flexibilidade, sendo amplamente aplicada para problemas mais complexos, uma vez que consegue abranger mais detalhes do ambiente real.

Seguindo esse contexto, utilizou-se a simulação como base de validação para o modelo proposto, apresentando resultados promissores para o desempenho operacional dos sistemas de manufatura. Além disso, o modelo é de fácil aplicação e entendimento, possibilitando ser adaptado e aplicado em diferentes cenários. Como ilustrado nos Capítulos 4 e 5, diferentes indicadores de desempenho podem ser ajustados às otimizações, proporcionando ganhos em diferentes óticas, segundo o interesse da organização.

Corroborando com os avanços tecnológicos nos ambientes de manufatura, as abordagens orientadas por dados proporcionam uma alocação de recursos mais eficientes. Nesse sentido, a proposta aqui apresentada contribui com uma programação preditiva-reativa orientada a dados de estoque, sequenciando de forma otimizada os trabalhos a serem processados, considerando os recursos disponíveis em tempo real. Com essa abordagem orientada a dados é possível ter uma melhor coordenação dos processos e tecnologias, oferecendo um sistema mais integrado, e aqui, especificamente, impacta positivamente no nível de serviço de entrega ao cliente.

Cabe destacar ainda que, a escolha de duas empresas brasileiras de médio porte para conduzir o caso teste e o estudo de caso, contribui para impulsionar a transformação digital proveniente da quarta revolução industrial nesses ambientes. Apesar dos conceitos da Indústria 4.0 serem explorados a uma década, no Brasil essa questão ainda está em processo evolutivo e o desenvolvimento de estudos científicos podem auxiliar no avanço da sua implementação.

Por fim, tanto as contribuições teóricas quanto as práticas têm um grande impacto positivo no ambiente industrial, ajudando a compreender os problemas inerentes à falta de material, reduzir a incerteza das informações e fornecer conhecimento sobre os dados do chão de fábrica. Esse conhecimento permite que os tomadores de decisões adaptem as programações mitigando por exemplo, o atraso no cumprimento dos pedidos. Além disso, permite que a tomada de decisão seja mais rápida e inteligente, apresentando soluções que melhorem a eficiência operacional do sistema de manufatura, promovendo competitividade para as empresas.

CAPÍTULO 7
7 CONCLUSÃO

O desenvolvimento desta tese buscou responder a seguinte questão de pesquisa: "*Como executar a programação da produção preditiva-reativa baseada em dados de forma a mitigar a não disponibilidade de material e aprimorar o desempenho operacional do sistema produtivo?*". Para responder a esta pergunta, foi desenvolvido um modelo de programação da produção preditiva-reativa orientada a dados de estoque provenientes do chão de fábrica. Com o modelo apresentado, o objetivo geral da tese foi alcançado. Além disso, para o desenvolvimento dessa proposta, este trabalho também elucidou o alcance de cada objetivo específico definido.

Para atingir o primeiro objetivo específico "*Identificar na literatura as principais abordagens referentes a programação da produção preditiva-reativa, bem como os principais métodos já adotados inerentes à sua implementação*", uma extensa revisão sistemática da literatura foi conduzida, conforme apresentada no Capítulo 3. Com isso, foi possível discutir a respeito da relevância de pesquisas nesse tema e apresentar as lacunas e oportunidades de pesquisas, além de explorar os métodos de implementação da programação da produção.

Com relação ao segundo objetivo específico "*Propor um modelo conceitual para a programação da produção preditiva-reativa orientada a dados de estoque*", este também foi alcançado, conforme exposto no Capítulo 3. Um modelo conceitual preliminar foi elaborado, apresentando uma ideia inicial e, posteriormente a revisão da literatura, uma versão final do modelo conceitual foi estabelecida. Este modelo conceitual foi estruturado conforme a evidência de poucos estudos considerando a estratégia preditiva-reativa para a programação da produção. Além disso, a programação da produção orientada a dados de estoque também foi constatada como uma oportunidade de pesquisa.

Seguindo para o terceiro objetivo específico "*Identificar na literatura as principais técnicas de machine learning para viabilizar a programação preditiva*", uma outra revisão sistemática da literatura foi conduzida, com o intuito de explorar as técnicas de ML mais adotadas na programação da produção. Os resultados deste estudo permitiram a escolha da técnica mais favorável a ser aplicada no modelo proposto, compondo o modelo conceitual consolidado no Capítulo 3. Dessa forma, é possível confirmar o cumprimento deste terceiro objetivo específico.

Avançando para o quarto objetivo específico "*Validar o método da otimização baseada em simulação para gerar a programação reativa*", este foi alcançado através do estudo apresentado no Capítulo 4. Neste estudo, um caso teste com dados reais de uma empresa brasileira foram utilizados para validar a programação reativa utilizando o SBO. Esta parte do modelo foi avaliada através de simulação computacional e os resultados alcançados foram promissores, conseguindo mitigar a quantidade de trabalhos atrasados perante a indisponibilidade de material. A programação reativa adotando o método SBO obteve em média, resultados superiores aos dos cenários em comparação. Esses resultados forneceram embasamento para manter a adoção do SBO para a programação reativa e assim, dar continuidade na elaboração do modelo final.

Finalmente, o quinto e último objetivo específico "*Mensurar o desempenho operacional do modelo desenvolvido por meio de simulação computacional, considerando um cenário real de uma empresa de manufatura*", foi cumprido com a validação do modelo final da tese através de um estudo de caso. Neste estudo, dados reais de outra empresa brasileira de médio porte do segmento metal-mecânico foram coletados e o modelo foi validado por meio de simulação computacional. Os resultados alcançados mostraram que, para o KPI de nível de serviço, o modelo é capaz de encontrar uma solução melhor do que os cenários comparados os quais utilizam regras fixas. Portanto, mesmo em um cenário dinâmico e estocástico, com quebras de máquinas, problemas de qualidade, atrasos de chegada da matéria-prima e falta de acuracidade no estoque, o modelo provou ser eficiente para mitigar os efeitos destas variações.

Adicionalmente, como a programação da produção é uma atividade importante, já que representa a conexão entre o planejamento e a produção no chão de fábrica, o modelo proposto apresentou através da estratégia preditiva-reativa uma programação eficiente, contribuindo para o sucesso dos modernos sistemas de manufatura. Além disso, como a programação influencia e é influenciada diretamente pelo estoque, a abordagem baseada em dados de estoque aqui proposta, é atraente para os tomadores de decisão. Ao utilizá-la, é possível obter soluções otimizadas para mitigar o atraso dos trabalhos que não foram produzidos devido à indisponibilidade da matéria-prima e alcançar um melhor nível de serviço. Este resultado tem um impacto positivo tanto no sistema de manufatura, pois mantém a produtividade e a eficiência diante de rupturas, quanto nos clientes, pois mitiga os atrasos na entrega.

Assim, pode-se constatar que esta tese cumpriu tanto o seu objetivo principal, quanto também os seus objetivos específicos. O Quadro 9 apresenta o resumo das publicações resultantes das fases desta tese. Sendo que, cada Fase foi associada a um ou mais objetivos específicos e cada um desses objetivos, contribuiu através do desenvolvimento de um artigo científico. Destaca-se aqui a relevância da elaboração da tese no formato de coletânea de artigos, pois com este modelo é possível submeter e divulgar para o meio acadêmico os estudos elaborados ao longo das fases da tese. Dessa forma, o benefício é duplo, para o meio acadêmico que recebe estudos de qualidade para aumentar o seu corpo de conhecimento, e para o pesquisador, que tem seus trabalhos reconhecidos e validados em importantes veículos científicos.

Quadro 9 – Resumo das publicações da tese

		ARTIGO	OBJETIVOS	REVISTA/CONGRESSO
FASE 1 (Capítulo 3)	Artigo 1.1	*Towards a data-driven predictive-reactive production scheduling approach based on inventory availability*	- Propor um modelo conceitual para a programação da produção preditiva-reativa orientada a dados de estoque	*9th IFAC Conference on Manufacturing Modelling, Management and Control (MIM 2019)* Acesso ao artigo: https://doi.org/10.1016/j.ifacol.2019.11.385
	Artigo 1.2	*Machine learning in production scheduling: an overview of the academic literature*	- Identificar na literatura as principais técnicas de *machine learning* para viabilizar a programação preditiva	*7th International Conference on Dynamics in Logistics (LDIC 2020)* Acesso ao artigo: https://doi.org/10.1007/978-3-030-44783-0_39
	Artigo 1.3	*Predictive-reactive production scheduling review: a conceptual model integrating inventory availability*	- Identificar na literatura as principais abordagens referentes a programação da produção preditiva-reativa - Identificar os principais métodos inerentes à sua implementação	Submetido para publicação.
FASE 2 (Capítulo 4)	Artigo 2	*Reactive production scheduling approach based on inventory availability*	- Validar o método da otimização baseada em simulação para gerar a programação reativa	*10th IFAC Conference on Manufacturing Modelling, Management and Control (MIM 2022) - IFAC-PapersOnLine* Artigo em fase de publicação.
FASE 3 (Capítulo 5)	Artigo 3	*An inventory data-driven approach for predictive-reactive production scheduling*	- Mensurar o desempenho operacional do modelo desenvolvido por meio de simulação computacional, considerando um cenário real de uma empresa de manufatura	Artigo em fase de submissão.

Fonte: Elaborado pela autora (2022).

7.1 LIMITAÇÕES E PESQUISAS FUTURAS

Embora esta tese tenha sido completamente concluída, como qualquer pesquisa, limitações são inerentes ao processo do estudo científico. Porém, tais limitações abrem novas perspectivas para estudos futuros.

Primeiramente, pode-se comentar como uma limitação a abrangência da revisão da literatura. Delimitações e decisões quanto à terminologia foram definidas, podendo ocasionar na perda e/ou exclusão indiretamente de alguns estudos sobre o tema. Então, novas revisões da literatura com diferentes critérios, podem incluir e explorar outros estudos, proporcionando mais corpo de conhecimento sobre o assunto.

Em segundo lugar, o modelo proposto limitou-se na composição da técnica de ANN com o GA para a programação preditiva e do método SBO para a programação reativa. Assim, novas técnicas de ML e de otimização podem ser testadas para validar a proposição do modelo. Além disso, a validação do modelo ocorreu em uma empresa do segmento metal-mecânico e seus resultados não podem ser generalizados para outros segmentos. Dessa forma, sugere-se a aplicação do modelo em empresas de outros setores, a fim de gerar uma comparação com os resultados aqui obtidos.

Como terceiro fator limitante, tem-se as regras de prioridade escolhidas para compor a programação da produção. Diversas regras são encontradas na literatura, além de estudos propondo adaptações às regras tradicionalmente aplicadas. No entanto, optou-se por utilizar regras padronizadas e já consolidadas na literatura, além de serem consideradas as mais usualmente aplicadas nos contextos industriais. Dessa forma, sugere-se a inclusão e aplicação de outras regras em pesquisas futuras, permitindo uma nova análise de resultados do modelo proposto.

Uma quarta limitação da pesquisa é com relação ao evento de ruptura considerado. Neste estudo, a ênfase estava na avaliação da capacidade de resposta da programação da produção reagir frente a indisponibilidade de material. Porém, no modelo de simulação desenvolvido, considerou-se também a quebra de máquina como um gatilho da programação reativa. No entanto, este evento foi implementado de forma determinística, ou seja, determinadas máquinas podiam falhar seguindo uma sequência pré-definida. Assim, pesquisas futuras podem avaliar o modelo incluindo estocasticidade nas quebras de máquinas, sendo uma consideração mais realista, além de englobar outros tipos de eventos de ruptura, como chegada de novos pedidos, cancelamento de pedidos, entre outros. Adicionalmente, estudos futuros também podem incorporar a análise de custos no modelo proposto. Assim, pode-se proporcionar vantagem na tomada de decisão, já que os ganhos financeiros atrelados à diminuição dos atrasos de entrega para os clientes ficariam evidentes.

Em quinto lugar, outra limitação apresentada neste estudo diz respeito ao nível operacional considerado, o qual se concentrou dentro de um sistema de manufatura. Dessa forma, como oportunidade de pesquisa futura, a abrangência de relacionamentos com empresas fornecedoras e clientes podem também favorecer tratativas para a falta de material.

Por fim, o sexto e último fator limitante foi a validação do modelo, realizada através de simulação computacional. Apesar do uso de simulação ser vantajoso para a pré-avaliação dos resultados da proposta, a sua implementação *in loco* não foi realizada. Assim, pesquisas futuras, podem viabilizar o desenvolvimento de parcerias com empresas que se interessem pela implementação do modelo. Com isso, estudos deverão ser conduzidos junto com os responsáveis das empresas, para projetar a execução prática do modelo em um sistema de manufatura real.

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Fonte: International Federation of Automatic Control, IFAC (2019).

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Artigo 1.2 – Machine Learning in Production Scheduling: An Overview of the Academic Literature (LDIC 2020, Springer)

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Artigo 2 – Reactive production scheduling approach based on inventory availability (IFAC-PapersOnLine)

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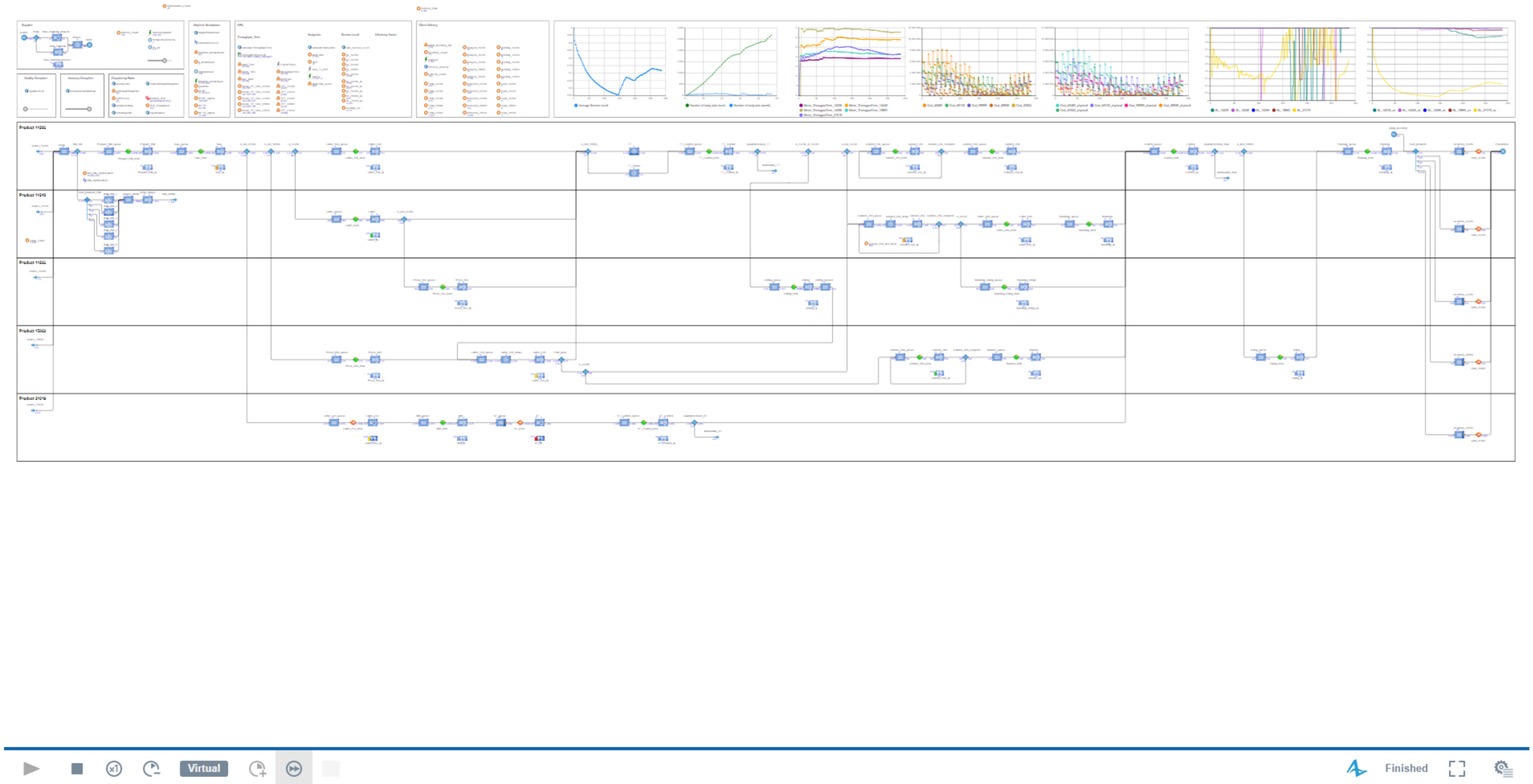

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