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Sincronização dinâmica de sistemas logísticos portuários inteligentes baseada no monitoramento do fluxo rodoviário

Florianópolis
2022

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

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

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

Florianópolis, 2022.

Dedico este trabalho ao meu irmão Álvaro Flores da Silva (*in memorian*), que sempre me apoiou e me incentivou a seguir a carreira acadêmica, além de servir como exemplo e inspiração para a minha vida.

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Aos meus irmãos, em especial ao Álvaro (*in memorian*) que tanto acreditou nos meus sonhos e me apoiou nos momentos de maior necessidade. Também aos meus sobrinhos e demais familiares que me apoiaram e compartilharam momentos de alegria e de tristeza comigo.

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“Foi o tempo que dedicaste à tua rosa que a fez tão importante”.

(Antoine de Saint-Exupéry)

RESUMO

O atual cenário vivenciado no setor portuário, onde os portos precisam desenvolver soluções que estejam de acordo com a demanda atual e mantendo um planejamento a longo prazo, está contribuindo para a transformação dos portos tradicionais modernos em Portos Inteligentes. Nesse contexto, um dos principais desafios para o ambiente portuário é controlar o fluxo de caminhões na sua hinterlândia, de modo a evitar congestionamentos que atrapalhem a circulação no entorno dos portos. Uma possível abordagem para lidar com esse cenário desafiador é a adoção de um Sistema de Agendamento de Caminhões que considere a possibilidade de reagendamentos, a partir da identificação de eventos disruptivos envolvendo os participantes do sistema logístico portuário. Dessa forma, o objetivo geral desta pesquisa é medir o impacto da utilização de um sistema flexível de atendimento de caminhões nos indicadores de desempenho logístico do sistema logístico portuário, baseado no compartilhamento de informações em tempo real. Os indicadores de desempenho logístico considerados neste estudo são número médio e máximo de caminhões em fila nos *gates* portuários, tempo médio e máximo de caminhões em fila e quantidade de caminhões atendidos fora da data agendada. O modelo conceitual desenvolvido para o funcionamento do Sistema Flexível de Agendamento de Caminhões consiste no uso de tecnologias inteligentes, como sensores, RFID, GPS, internet, OCR, *gate* automatizado, IoT e *Big Data*, que são integradas à um algoritmo de *Machine Learning* para prever a condição do caminhão ao longo do transporte e classificar o caminhão entre antecipado, na janela, e atrasado. Usando o método de pesquisa de modelagem quantitativa e o emprego de Simulação de Eventos Discretos na linguagem de programação do *software* R®, este estudo performou um caso teste em um terminal portuário brasileiro para comparar o método proposto com um cenário estático, sem uso de tecnologia inteligente e sem a possibilidade de reagendamento, e um cenário intermediário, considerando tecnologia inteligente, mas sem a possibilidade de reagendamento. O modelo de *Decision Tree*, algoritmo de *Machine Learning*, utilizou cerca de 250 mil dados para treinamento e atingiu uma acuracidade de 95,37% para classificação da condição dos caminhões. A simulação do cenário com TAS dinâmico obteve os melhores índices para os cinco indicadores definidos, reduzindo o tempo médio de espera dos caminhões em 90,4% em comparação com o primeiro cenário, resultando em uma melhor distribuição de chegadas e impacto monetário nas operações do terminal portuário, já que a sincronização possibilita o aumento da capacidade de atendimento. Dessa forma, o método construído demonstrou eficiência para sincronizar o sistema logístico portuário a partir do monitoramento de informações rodoviárias em tempo real. A união de tecnologias inteligentes com o uso de métodos flexíveis é uma oportunidade de alcançar resultados significativamente positivos em ambientes portuários e oferecer benefícios para os membros do sistema logístico. Assim, essa dissertação aborda contribuições teóricas para a discussão científica sobre o conceito de Porto Inteligente, assim como a integração de informações no sistema logístico portuário para a formação de reagendamento flexível.

Palavras-chave: Portos Inteligentes. Sistema de Agendamento de Caminhões. Sincronização dinâmica.

ABSTRACT

The current scenario experienced in the port sector, where ports need to develop solutions that are in line with current demand and maintaining long-term planning, is contributing to the transformation of modern traditional ports into Smart Ports. In this context, one of the main challenges for the port environment is to control the truck flow at port hinterland, in order to avoid traffic congestions that hinder circulation around the ports. A possible approach to deal with this challenging scenario is the adoption of a Truck Appointment System that considers the possibility of rescheduling, based on the identification of disruptive events involving the members of port logistics system. Thus, the main objective of this research is to measure the impact of using a flexible truck service system on the logistics performance indicators of the port logistics system, based on real-time information sharing. The key performance indicators considered in this study are the average and maximum number of trucks in queue at port gates, average and maximum time of trucks in queue and number of trucks served outside the scheduled time window. The conceptual model developed for the functioning of the Flexible Truck Appointment System consists of the use of smart technologies, such as sensors, RFID, GPS, internet, OCR, automated gate, IoT and Big Data, which is integrated with a Machine Learning algorithm for predict the condition of the truck during the transport to the port and classify the truck in on-schedule, early or late. Using the quantitative modeling research method and the use of Discrete Event Simulation in the R® software programming language, this study used a test case of a Brazilian port terminal to compare the proposed method with a static scenario, without the use of smart technologies and without the possibility of rescheduling, and an intermediate scenario, considering smart technology but without the possibility of rescheduling. The Decision Tree model, a Machine Learning algorithm, used around 250,000 historical data for training the model and reached an accuracy of 95.37% for classifying the condition of trucks. The simulated scenario considering the flexible TAS obtained the best rates for the five defined indicators, reducing the average waiting time of trucks by 90.4% compared to the current scenario, in addition to avoiding the existence of peak hours with congestion from balancing arrivals in time windows with limited appointments. Thus, the constructed method demonstrated efficiency in synchronizing the port logistics system from the monitoring of road information in real time. The integration of smart technologies with the use of flexible methods is an opportunity to achieve significantly positive results in port environments and offer benefits to members of the logistics system. Thus, this dissertation addresses theoretical contributions to the scientific discussion on the concept of Smart Port, as well as the integration of information in the port logistics system for the development of a flexible schedule.

Keywords: Smart Ports. Truck Appointment System. Dynamic synchronization.

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LISTA DE ABREVIATURAS E SIGLAS

ABS	*Agent-based Simulation*
AGVs	*Automated Guided Vehicles*
API	*Application Programming Interface*
CAPES	Coordenação de Aperfeiçoamento de Pessoal de Nível Superior
DES	*Discrete Event Simulation*
DSS	*Decision Support System*
DTAS	*Static Truck Appointment System*
FMS	*Flexible Manufacturing System*
GA	*Genetic Algorithm*
GPS	*Global Positioning System*
IA	Inteligência Artificial
IoT	Internet of Things
KPI	*Key Performance Indicators*
OCR	*Optical Character Recognition*
PPGEP	Programa de Pós Graduação em Engenharia de Produção
PRISMA	*Preferred Reporting Items for Systematic Review and Meta-Analysis*
RFID	*Radio Frequency Identification*
RSL	Revisão Sistemática de Literatura
STAS	*Static Truck Appointment System*
TAS	*Truck Appointment System*
TEUs	*Twenty-foot Equivalent Unit*
UNCTAD	*United Nations Conference on Trade and Development*

SUMÁRIO

1 INTRODUÇÃO

O capítulo de introdução está dividido em: contextualização, objetivos, justificativa do tema, delimitação do estudo e estrutura.

1.1 CONTEXTUALIZAÇÃO

A emergente integração da economia mundial e o crescimento da cooperação comercial entre países de diferentes continentes, nas últimas décadas, tem proporcionado um aumento das oportunidades de comércio exterior para os países subdesenvolvidos (CHEN *et al.*, 2019). Jović *et al.* (2019) destacam que o desaparecimento das fronteiras entre países, no que tange as relações comerciais, acarretou um aumento do volume de cargas movimentadas nos terminais portuários, trazendo um conjunto de desafios para as autoridades portuárias.

Nesse contexto, um dos principais desafios apresentados por Yau *et al.* (2020) para o ambiente portuário é controlar o fluxo de veículos na sua hinterlândia, de modo a evitar congestionamentos que atrapalhem a circulação no entorno dos portos. Um fator que agrava o problema de fluxo de veículos é referente à restrição de espaço físico disponível para os terminais portuários, que frequentemente estão localizados em áreas urbanas, tornando necessária a adoção de medidas inteligentes, tendo em vista que a expansão da capacidade de atendimento, por meio de estrutura física, não pode ser realizada (HANSCHKE; HEITMANN; RENNER, 2016; RAJABI *et al.*, 2019).

Segundo Molavi *et al.* (2020), esse cenário desafiador, onde os portos precisam desenvolver soluções que estejam de acordo com a demanda atual e mantendo um planejamento a longo prazo, está contribuindo para a transformação dos portos tradicionais modernos em portos inteligentes. Por ser um assunto recente na literatura, a definição e as tecnologias que tornam um porto inteligente ainda não são um consenso (JUN; LEE; CHOI, 2018). Contudo, na sua definição mais básica, um porto inteligente pode ser caracterizado como um novo modelo de gerenciamento portuário, com base no uso de ferramentas inovadoras e tecnológicas (KARAŚ, 2020).

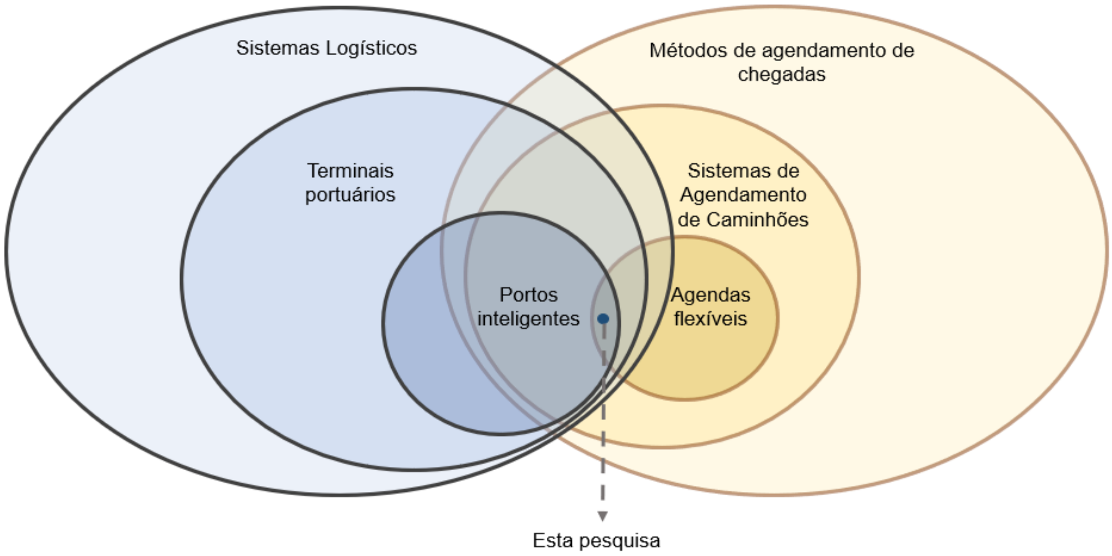
Alguns terminais portuários que estão adotando tecnologias inteligentes nas suas operações são os portos de Rotterdam, Hamburgo e Singapura (DURÁN; CÓRDOVA; PALOMINOS, 2019). Como resultado da adoção dessas tecnologias, Alop (2019) relata que é possível perceber uma redução significativa do congestionamento na hinterlândia portuária e uma minimização da quantidade de cargas armazenadas nesses portos. Essa afirmação permite inferir que a sincronização da movimentação entre membros do sistema logístico portuário permite um controle do momento de chegada dos veículos, reduzindo o congestionamento na entrada dos portos, e, ainda, garante uma confiabilidade do processo, resultando em cargas sendo entregues mais próximas do prazo de embarcação, o que reduz o seu tempo de armazenamento nas instalações dos terminais.

Entretanto, Frazzon *et al.* (2019) alertam que apenas a adoção de tecnologias inteligentes não é suficiente para solucionar os problemas operacionais dos portos, especialmente devido ao aumento de demanda e propõem a aplicação, em conjunto, de planejamento avançado, programação de agenda e monitoramento de fluxos de veículos com destino à área portuária. Sistemas de Agendamento de Caminhões, mundialmente conhecidos como *Truck Appointment Systems* (TAS), costumam ser uma abordagem comum para reduzir o congestionamento e o tempo de espera nos terminais portuários (MAR-ORTIZ; CASTILLO-GARCÍA; GRACIA, 2020).

Apesar dos benefícios dos TAS, a existência de uma rigidez quanto aos horários agendados, sem espaço para ocorrência de imprevistos, pode acarretar conflitos entre o terminal portuário e as empresas transportadoras de cargas. Sun, Lang e Wang (2016) alegam que os sistemas de agendamento são mais adequados quando integram flexibilidade. Sendo assim, um TAS pode obter resultados mais satisfatórios para os envolvidos no sistema logístico portuário quando empregado com flexibilidade resultante de estratégias obtidas com o acompanhamento de tecnologias (SOUIER; DAHANE; MALIKI, 2019). Ainda, Castilla-Rodríguez *et al.* (2020) afirmam que o método de *Discrete Event Simulation* (DES) fornece ferramentas adequadas para o estudo desse problema de maneira natural.

Diante do exposto, esta pesquisa está inserida no contexto da combinação de tecnologias inteligentes e métodos flexíveis de TAS em terminais portuários, visando reduzir o congestionamento na hinterlândia dos portos. A Figura 1 demonstra a localização do tema estudado dentro dos conceitos abordadas neste estudo, relacionando as áreas de gerenciamento de sistemas logísticos no setor portuário, utilizando o contexto da adoção de tecnologias inteligentes para processos decisórios em portos e métodos flexíveis para a construção de um Sistema de Agendamento de Caminhões.

Figura 1 - Contextualização da pesquisa nas temáticas deste projeto



Fonte: Elaborado pelo autor (2022).

Assim, o presente estudo aborda o desenvolvimento de um método de sincronização dinâmica, possibilitando adaptações em tempo real, do sistema logístico portuário, a partir da combinação de tecnologias inteligentes, que caracterizam o conceito de Portos Inteligentes na Indústria 4.0. Essa integração de informações entre os membros do sistema logístico portuário tem o intuito de fornecer maior flexibilidade no agendamento e operação do TAS dos portos, beneficiando os terminais portuários e os usuários do sistema.

1.2 OBJETIVOS

Os objetivos deste estudo estão dispostos de forma a fornecer as informações necessárias quanto ao que se pretende alcançar com a realização do mesmo. Estes objetivos estão divididos em objetivo geral e objetivos específicos, conforme apresentados nos tópicos a seguir.

1.2.1 Objetivo Geral

O objetivo geral deste estudo é desenvolver um sistema flexível de atendimento de caminhões e medir o impacto da sua utilização nos indicadores de desempenho logístico do sistema logístico portuário, baseado no compartilhamento de informações em tempo real. Os indicadores de desempenho logístico considerados são: número médio e máximo de caminhões em fila nos *gates* portuários, tempo médio e máximo de caminhões em fila e quantidade de caminhões atendidos fora da data agendada.

1.2.2 Objetivos Específicos

Visando atingir o objetivo geral proposto por este estudo, os objetivos específicos foram definidos como:

a) Definir o conceito de Porto Inteligente e apresentar as tecnologias inteligentes com melhores resultados na redução de congestionamento na hinterlândia portuária;
b) Identificar métodos flexíveis de agendamento de chegadas em diferentes ambientes, desde que o método permita a adaptação para o contexto portuário;
c) Propor um Sistema de Agendamento de Caminhões capaz de identificar eventos disruptivos e automaticamente reagendar o cronograma de chegadas, baseado em informações coletadas de tecnologias inteligentes no terminal portuário e nos membros do seu sistema logístico;
d) Comparar, por meio de Simulação de Eventos Discretos, indicadores de desempenho logístico operacionais e estratégicos do atendimento de caminhões em diferentes cenários, considerando atendimento estático e dinâmico.

1.3 JUSTIFICATIVA DO TEMA

A indústria portuária está vivenciando um cenário de transformação com a construção de portos inteligentes, como resultado de avanços tecnológicos, levando os terminais portuários para uma nova era, caracterizada pelo aumento de confiabilidade e eficiência em processos operacionais (MOLAVI *et al.*, 2020). Essa transformação origina a necessidade de escolha de soluções tecnológicas adequadas para o contexto operacional, de acordo com os desafios portuários, requerendo uma integração de tecnologias entre o porto e os membros do seu sistema logístico (KARAŚ, 2020).

Em contrapartida, o resultado da falta de sincronização no processo de chegada de veículos costuma resultar em um gargalo no sistema logístico, especialmente com o constante aumento da demanda dos terminais portuárias nos últimos anos (LAZAROIU; ROSCIA, 2017; YAU *et al.*, 2020). Assim, a ausência de iniciativas operacionais sincronizadas que possibilitem a tomada de decisão quanto às restrições de infraestrutura, causa congestionamento nos acessos portuários, além de afetar o ambiente e a sociedade em que o porto está inserido (FRAZZON *et al.*, 2019).

Nesse sentido, estratégias de gestão portuária contribuem para evitar ociosidade e congestionamento, a partir do controle das operações e decisões quanto à capacidade do porto para que haja uma configuração ótima dos recursos (TRISKA; FRAZZON; SILVA, 2020). Uma das principais estratégias a ser estudada refere-se à eficiente coordenação do tráfego de caminhões na área portuária, especialmente no contexto de portos que buscam uma versatilidade em suas operações (TADUMADZE *et al.*, 2019).

Na literatura relativa à temática portuária, o problema de definição de agenda de caminhões tem recebido atenção frequente devido ao seu relevante potencial em operações logísticas (BOYSEN; FLIEDNER, 2010). Adicionalmente, as mudanças da demanda de mercado têm se tornado cada vez mais imprevisíveis e abruptas (DANG; NGUYEN; RUDOVÁ, 2019), caracterizando um cenário onde sistemas flexíveis, que permitem uma adaptação conforme a identificação de circunstâncias não planejadas, passam a ser mais importantes, especialmente na era da Indústria 4.0 e aplicação de conceitos inteligentes (LU, 2017).

Nesse cenário de imprevisibilidade, a pandemia do COVID-19 explicitou ainda mais a necessidade de flexibilidade nos sistemas logísticos e nas cadeias de suprimentos globais, colocando em evidência a primordialidade de serviços rápidos e com alta capacidade de resposta frente a eventos disruptivos (DENTE; HASHIMOTO, 2020; SHOKRANI *et al.*, 2020). Assim, métodos tecnológicos e flexíveis para o gerenciamento de sistemas logísticos passam a ganhar um destaque ainda maior.

Nesse contexto, embora tenham sido encontrados trabalhos que propõem métodos de agenda flexíveis para o contexto portuário, não foram evidenciados estudos que integram o uso de tecnologias inteligentes e Sistemas de Agendamento de Caminhões, com o intuito de fornecer flexibilidade e sincronização para o sistema logístico portuário, caracterizando uma área de pesquisa com potencial a ser explorado. Dessa forma, a contextualização da pesquisa dentro de um campo de estudo emergente e com urgência de soluções potencializada pelo cenário do surgimento do COVID-19, onde sistemas portuários flexíveis e com alta capacidade de resposta passam a ser requisitados, justifica a temática deste estudo, apoiada pela literatura revisada.

1.4 DELIMITAÇÃO DO ESTUDO

O presente estudo está inserido no campo de concentração de logística e transporte, tendo como linha de pesquisa a análise, otimização e gerenciamento de cadeias logísticas. Ademais, o estudo está delimitado à construção de um Sistema de Agendamento de Caminhões flexível e capaz de promover reagendamentos perante a ocorrência de eventos disruptivos envolvendo participantes do sistema logístico portuário. Ainda, quando refere-se ao sistema logístico portuário, esta pesquisa está limitada em considerar o fluxo de operações e informações entre os participantes do sistema rodoviário, envolvendo caminhões transportadores de carga e o terminal portuário.

Do ponto de vista teórico, a revisão de literatura adotou o critério de inclusão de limitar artigos publicados em língua inglesa e em revistas. Ademais, as bases de dados selecionadas para este estudo foram *Scopus* e *Web of Science*.

1.5 ESTRUTURA

A estrutura adotada neste estudo segue a forma de coletânea de artigos, em conformidade com a resolução vigente 002/PPGEP/2018, aprovada em 07 de novembro de 2018 e disponibilizada no site do Programa de Pós Graduação em Engenharia de Produção (https://ppgep.ufsc.br/resolucoes-e-outros/). As definições de padrões de formatação seguidos nesta pesquisa são as seguintes:

e) Os capítulos 1, 2, 3, 6 e 7 são escritos em língua portuguesa, enquanto os capítulos 4 e 5 são apresentados em língua inglesa, por se tratarem de artigos submetidos a revistas internacionais;
f) As referências utilizadas para a escrita dos capítulos de introdução, referencial teórico e os métodos e técnicas de pesquisa são apresentadas após o capítulo 7, seguindo a formatação ABNT;

g) As referências presentes nos artigos retratados nos capítulos 4 e 5 são apresentadas ao final de cada artigo, mantendo o padrão específico de submissão;
h) A numeração de elementos como Figuras e Tabelas apresentadas no artigo segue a contagem própria dos capítulos 4 e 5, de forma a manter a estrutura de submissão;

Sendo assim, o presente estudo foi estruturado em 7 capítulos. O capítulo 1 apresenta uma contextualização da área de concentração do problema estudado, os objetivos, divididos em objetivo geral e objetivos específicos, a justificativa do tema, a delimitação do tema e a estrutura. No capítulo 2 é apresentado o referencial teórico que apresenta conceitos dos temas tratados neste estudo e suporta as decisões metodológicas. O capítulo 3 relata os métodos e técnicas de pesquisa utilizados para a construção deste estudo, assim como um detalhamento do procedimento metodológico e a apresentação do caso teste. O capítulo 4 exibe o primeiro artigo resultante deste estudo, que consiste na estruturação do modelo conceitual a partir das revisões de literatura executadas. O capítulo 5 apresenta o segundo artigo oriundo deste estudo, abordando a tradução do modelo conceitual em um modelo computacional e os resultados da simulação do método proposto em um caso teste. O capítulo 6 retrata uma síntese dos resultados deste estudo. Por fim, o capítulo 7 sumariza as considerações finais deste trabalho e detalha as oportunidades de estudos futuros a partir dos resultados alcançados.

2 REFERENCIAL TEÓRICO

Nesta seção é apresentado o referencial teórico elaborado a partir da literatura revisada, possuindo o intuito de fornecer o embasamento científico para a execução do estudo. Destaca-se que o artigo 1, apresentado na seção 4, retrata uma revisão mais aprofundada em relação aos Portos Inteligentes, tecnologias portuárias inteligentes e métodos flexíveis de atendimento. Dessa forma, a revisão de literatura apresentada nesta seção limita-se aos sistemas logísticos portuários e Sistema de Agendamento de Caminhões adaptativo, com a finalidade de complementar o embasamento teórico e evitar repetição de assuntos.

2.1 SISTEMAS LOGÍSTICOS PORTUÁRIOS

O sistema logístico portuário refere-se a estrutura formada por membros e mecanismos envolvidos no processo de transporte de cargas, seja por meio terrestre ou marítimo, desde que o terminal portuário atue como ponto central nas operações de transporte (BO; MEIFANG, 2020). Devido ao foco desta pesquisa estar nas operações que envolvem os membros do sistema logístico portuário terrestre, os membros envolvidos nas operações marítimas não serão considerados no estudo desenvolvido. Diante do exposto, Simão (2012) aponta que o sistema logístico portuário é formado principalmente por quatro membros: expedidores, transportadores, terminais portuários e consignatários.

Ainda, Simão (2012) relata a função e representatividade de cada um desses quatro atores do sistema logístico. Inicialmente, os expedidores são o ponto de origem da carga, ou seja, em muitos casos é o próprio fabricante ou produtor da carga movimentada. Na sequência, os transportadores terrestre são representados pelas empresas de transporte contratadas para fazer a transferência da carga do ponto de origem até o terminal portuário e/ou do terminal portuário até o ponto de destino, sendo, no contexto estudado, os caminhões. O terceiro ator do sistema logístico é o próprio terminal portuário, que além da coordenação e sincronização da movimentação de carga, desempenha a função de identificação, rastreabilidade, armazenagem, embalagem, manuseio, transporte e expedição. No ponto final do sistema logístico portuário terrestre encontram-se os consignatários, caracterizados como o destino final da carga movimentada.

Em relação à hinterlândia e o seu papel no sistema logístico portuário, Sdoukopoulos e Boile (2020) afirmam que o conceito de hinterlândia portuária é altamente dinâmico e complexo, além de que a eficiência da operação nessa área possui influência direta na competitividade entre portos. Enquanto na perspectiva da autoridade portuária, a delimitação da hinterlândia é feita a partir das áreas que são atraídas pelos serviços do porto, a perspectiva do transportador sugere que essa demarcação deve ocorrer com base nas parcerias e conexões entre portos e demais membros do sistema logístico portuário, ou seja, os acordos de exportação firmados entre portos são responsáveis pela limitação da área de atuação da hinterlândia de cada terminal portuário (NOTTEBOOM *et al.*, 2013; SDOUKOPOULOS; BOILE, 2020).

No contexto de delimitação de hinterlândia baseada nas conexões entre terminais e *stakeholders*, fica evidente a necessidade de integração de operações e compartilhamento de informações entre membros do sistema logístico, visando garantir um planejamento, previsão e gerenciamento de atividades mais eficiente (HAN, 2018; RAGATZ; HANDFIELD; PETERSEN, 2002). Ainda, esse cenário de integração entre membros do sistema logístico promoveu uma evolução nas funções e características dos terminais portuários e demais integrantes do sistema, onde os portos deixam de ter apenas a responsabilidade de transporte e armazenamento de cargas para exercerem funções gerenciais sincronizadas com os demais atores envolvidos nos processos portuários (BO; MEIFANG, 2020; HAN, 2018).

Dessa forma, o advento de conceitos da Indústria 4.0 no setor portuário, experenciado desde o início da década de 2010, ofereceu a oportunidade de adoção de tecnologias modernas e inteligentes, visando suprir a necessidade de integração de informações entre membros do sistema logístico, ao passo que oferecerem respostas eficientes frente à existência de eventos disruptivos de demanda (HOSSAIN *et al.*, 2020). Ainda, Bo e Meifang (2020) sugerem que a existência de fluxos e movimentação de carga sincronizados requer um relacionamento cooperativo e com o compartilhamento de informações em tempo real entre os terminais portuários e as empresas transportadoras de carga.

De outro lado, a falta de integração de sistemas logísticos em cenários instáveis e sujeitos a alterações rápidas no contexto global de movimentação de cargas, como é o caso do setor portuário, é capaz de acarretar problemas, como perdas econômicas e de competividade, além de congestionamento na hinterlândia portuária (FRAZZON *et al.*, 2019; HOSSAIN *et al.*, 2020). No sentido de congestionamentos, o compartilhamento de informações entre membros do sistema logístico em tempo real é uma estratégia de sucesso para garantir a coordenação de veículos e que o fluxo de caminhões transportadores em direção a área portuária não seja superior a capacidade de atendimento (BARON; MATHIEU, 2010; KARAŚ, 2020).

Assim sendo, em cenários de integração do sistema logístico portuário, os portos operam sob a função de ponto central de conexão das informações dos *stakeholders* envolvidos nos processos, visando coordenar os serviços oferecidos pelos terminais portuários e manter alta eficiência nas operações (SHAO, 2016). Um exemplo de sistema logístico portuário com integração das informações dos *stakeholders* foi desenvolvido pelo Porto de Hamburgo, recebendo o nome de *smartPORT logistics* (SPL). O projeto desenvolvido pelo porto alemão consiste na integração de informações das empresas de transporte de carga, por meio da atualização de motoristas dos caminhões, e tecnologias inteligentes instaladas próximas à área portuária, como torres de identificação de rádio frequência, para otimizar as rotas de tráfego dos veículos, reduzindo o tempo de transporte e evitando situações de congestionamento na área portuária (HEILIG; LALLA-RUIZ; VOß, 2017).

Ainda no sentido de projetos de integração de informações entre membros do sistema logístico, Amodu e Othman (2018) visualizam uma tendência de fornecer inteligência aos sistemas logísticos e sugerem que a inteligência desses sistemas está atrelada à habilidade de operação de meios de comunicação e transmissão de informações de forma automática entre indivíduos envolvidos nos processos logísticos. Essa integração de informações dinâmica é possível por meio de *softwares* e programas conectados à internet, onde o fluxo de dados pode ser acessado por múltiplos servidores e suportar o processo decisório dos membros do sistema logístico (BAG *et al.*, 2020; MONTORI *et al.*, 2018).

Uma possibilidade de sistemas logísticos inteligentes consiste na utilização de abordagens de aprendizado, em que o algoritmo de controle do sistema portuário consegue, de forma automática, identificar padrões e definir as melhores estratégias de solução de problemas, com base em dados históricos de informações dos membros envolvidos no processo (BO; MEIFANG, 2020; YU *et al.*, 2019). Iranezzhad, Prato e Hickman (2020) desenvolveram um algoritmo de aprendizado, suportado por uma base de dados de decisões estratégias tomadas por humanos, para promover inteligência ao sistema logístico de um terminal portuário na identificação de movimentação otimizada de contêineres e utilização de caminhões de empresas parceiras do porto.

Outra possibilidade apresentada por Bag *et al.* (2020) é a adoção de sistemas logísticos orientados em Inteligência Artificial (IA) e *Internet of Things* (IoT) para combinar dados de diferentes elementos e/ou mecanismos, enviar informações precisas para processos seguintes e possibilitar uma adaptação autônoma dos sistemas logísticos. Ainda, sistemas logísticos baseados em IoT podem ser usados para identificar, comunicar ou gerenciar estruturas globais por meio da conectividade entre objetos e sistemas físicos e virtuais (ČOLAKOVIĆ; HADŽIALIĆ, 2018).

De acordo com o exposto, é possível visualizar os terminais portuários como atores centrais do sistema logístico portuário e principal responsável pela utilização de sistemas inteligentes, tendo em vista que estão diretamente conectados com os *stakeholders* envolvidos no sistema. Assim, a adoção de conceitos e tecnologias inteligentes, dentro do contexto da Indústria 4.0, devem ter a implementação coordenada pelos portos. No próximo tópico serão apresentados temas relacionados a estruturação de um Sistema Flexível de Agendamento de Caminhões.

2.2 SISTEMA FLEXÍVEL DE AGENDAMENTO DE CAMINHÕES

Truck Appointment System (TAS) é uma abordagem de atendimento utilizada pelos terminais portuários para reduzir o tempo de espera dos caminhões em fila para entrar no porto, e, assim, evitar a existência de congestionamento na hinterlândia portuária, por meio do recebimento antecipado de informações, que permitem um planejamento mais eficiente das autoridades portuárias (MAR-ORTIZ; CASTILLO-GARCÍA; GRACIA, 2020). O uso de TAS em terminais portuários surgiu no início dos anos 2000 em portos localizados na Califórnia, nos Estados Unidos da América, com o intuito de balancear a chegada de caminhões ao longo do dia e reduzir o congestionamento nos *gates* portuários (HUYNH; SMITH; HARDER, 2016).

Desde então, diversos terminais portuários ao redor do mundo aderiram ao uso de TAS para coordenar o fluxo de veículos e estudos para analisar e propor metodologias de otimização dos agendamentos passaram a ser difundidos no campo científico (ISLAM; OLSEN; DAUD AHMED, 2013). Alguns estudos de caso aplicados por pesquisadores que validam a eficiência do uso de TAS em terminais portuários podem ser visualizados nos trabalhos de Giuliano e O’Brien (2007), Maguire *et al.* (2010), Zhang, Zeng e Chen (2013) e Zehendner e Feillet (2014).

Embora os TAS apresentem resultados positivos, a crescente demanda de serviços portuários e o aumento da competitividade no setor evidenciaram uma necessidade de adoção de agendamentos flexíveis, ao invés das metodologias de agendamento estáticas (SUN; LANG; WANG, 2016). Além de proporcionar mais eficiência para os terminais portuários, um sistema de agendamento flexível possibilita benefícios de redução de penalidades para as empresas transportadoras, já que diversos portos cobram taxas para realizar atendimentos com atraso, o que não costuma ocorrer em sistemas que permitam reagendamentos (HUYNH; SMITH; HARDER, 2016).

Visando propor métodos flexíveis, o estudo de Li *et al.* (2018) busca identificar estratégias para minimizar o impacto dos eventos disruptivos com maior ocorrência em terminais portuários, buscando integrar os resultados da identificação dos eventos disruptivos no sistema de agendamentos a partir da sugestão de formas de aumentar a capacidade de resposta frente a esses acontecimentos. Os eventos disruptivos mencionados são referentes à ocorrência de episódios que impossibilitam a correta execução do planejamento dos atendimentos e as medidas de aumentar a capacidade de resposta do sistema logísticos são relativas à estruturação de abordagens de previsão e antecipação de possíveis acontecimentos não planejados para minimizar o tempo necessário de busca de soluções alternativas, quando os eventos ocorrem (ALI; MAHFOUZ; ARISHA, 2017; LI *et al.*, 2018; PETTIT; CROXTON; FIKSEL, 2013).

De maneira similar, Caballini *et al.* (2018) realizam um estudo de modelagem matemática para relacionar os agendamentos com as informações de localização da carga, computando, portanto, um tempo de atraso aceitável para cada caminhão dentro do sistema de agendamentos. Visando relacionar diretamente o TAS com os recursos disponíveis e o atendimento de navios para tornar o sistema mais adaptativo, Mar-Ortiz, Castillo-García e Gracia (2020) apresentam um *Decision Support System* (DSS) para estabelecer cotas diárias de atendimento de caminhões e controlar, de maneira eficiente, o fluxo de caminhões na hinterlândia portuária.

Além das abordagens já mencionadas para tornar os TAS mais flexíveis, os estudos de Huynh (2009) e de Phan e Kim (2015) demonstram estratégias de inserir adaptações nos agendamentos sem prejudicar o sistema. No estudo de Huynh (2009) é considerada a possibilidade de agendamentos em lotes, em que um número pré-definido de caminhões organiza as reservas de atendimento dentro de um intervalo de tempo, mas sem definir a ordem de atendimento entre os caminhões integrantes do lote. Já no estudo de Phan e Kim (2015) é proposto um sistema de negociação e alteração de horários de atendimento entre os próprios caminhões, em que o terminal portuário apenas é comunicado das alterações e efetua os atendimentos.

Em paralelo, no contexto dos Portos Inteligentes o uso de tecnologias passou a ser uma ferramenta de suporte aos sistemas de agendamento. Nesse sentido, o estudo de Heilig, Lala-Ruiz e Voß (2017) adota o uso de tecnologias de integração de informação para propor um sistema de roteamento de veículos no transporte entre terminais, empregando algoritmos híbridos de simulação para identificar a configuração ótima de agendamentos nos terminais a partir das rotas dos veículos. Ademais, a adoção de ferramentas tecnológicas para os agendamentos e atendimentos em terminais portuários é abordada por Mar-Ortiz *et al.* (2018), que relatam que os avanços tecnológicos e o emprego de tecnologias inteligentes proporcionam melhores condições para o desenvolvimento de soluções em tempo real.

Sendo assim, é possível perceber que o advento da Indústria 4.0, que proporcionou o surgimento de tecnologias inteligentes e o conceito de Portos Inteligentes, representa uma oportunidade de ganho para a sincronização dos sistemas logísticos portuários, por meio do desenvolvimento de TAS que possibilitem uma adaptação dos agendamentos frente à identificação de eventos disruptivos, monitorados e gerenciados por tecnologias inteligentes. Portanto, algoritmos e sistemas integrando informações de *stakeholders* terrestres do sistema logístico portuário para organizar, em tempo real, os agendamentos e atendimentos dos *gates* portuários representam um campo de pesquisa capaz de prover resultados satisfatórios para a sincronização dinâmica de sistemas logísticos portuários inteligentes.

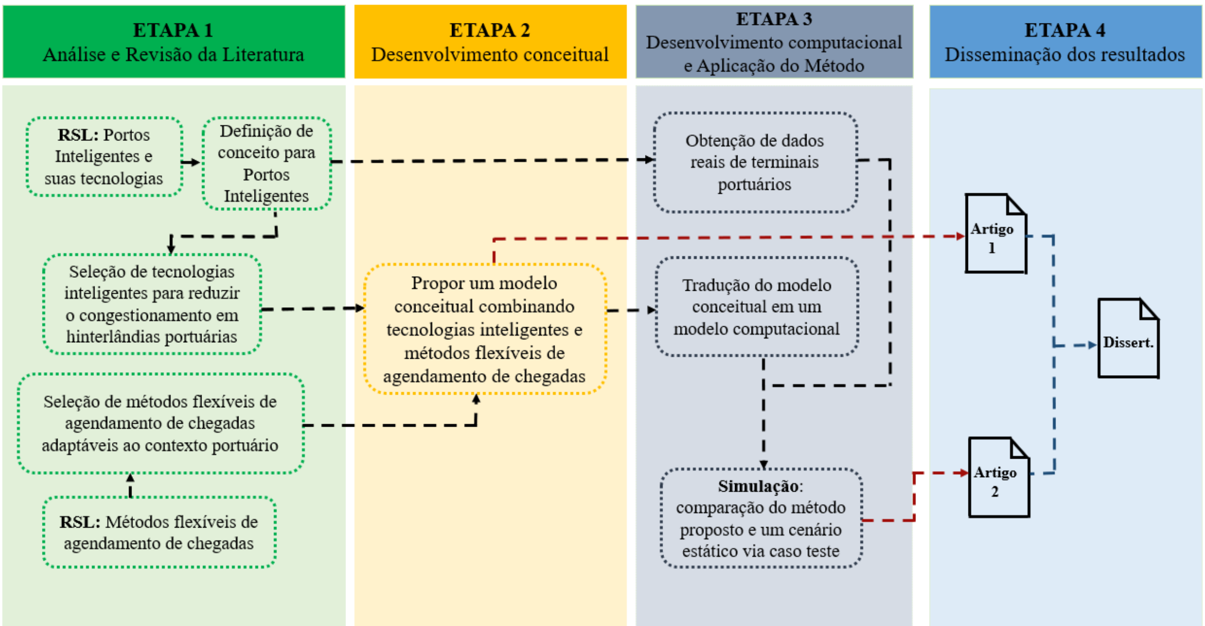
3 METODOLOGIA

Nesta seção são apresentados os procedimentos metodológicos, a abordagem proposta para atingir os objetivos deste estudo e as informações referentes ao caso teste.

3.1 PROCEDIMENTOS METODOLÓGICOS

Os procedimentos metodológicos propostos neste estudo possuem o intuito de garantir a correta execução dos objetivos específicos apresentados na Seção 2 deste trabalho. Sendo assim, este estudo está dividido em quatro etapas principais: (i) Análise e revisão da literatura existente; (ii) Desenvolvimento conceitual; (iii) Desenvolvimento computacional e aplicação do método; e, (iv) Disseminação dos resultados. O fluxograma, exposto na Figura 2, detalha as etapas desempenhadas neste estudo.

Figura 2 - Procedimento metodológico proposto



Fonte: Elaborado pelo autor (2022).

Conforme demonstrado na Figura 2, a execução das atividades que compõem as etapas 1 e 2 podem ser realizadas em paralelo, como a revisão sistemática de Portos Inteligentes e suas tecnologias e a revisão sistemática de métodos flexíveis de agendamento de chegadas. Adicionalmente, visando relacionar as etapas do procedimento metodológico proposto com os objetivos específicos deste estudo é apresentado o Quadro 1.

Quadro 1 - Relação entre etapas, métodos, objetivos e publicações deste estudo

Etapa	Método empregado	Objetivo específico relacionado	Diss. dos resultados
1. Análise e Revisão da Literatura	Revisão sistemática da literatura	i. Definir o conceito de porto inteligente e apresentar as tecnologias inteligentes com melhores resultados na redução de congestionamento nas portarias de terminais portuários; ii. Identificar métodos flexíveis de agendamento de chegadas que podem ser traduzidos em um Sistema de Agendamento de Caminhões no contexto portuário	Artigo 1
2. Desenvolvimento conceitual	Modelagem conceitual	iii. Propor um Sistema de Agendamento de Caminhões capaz de identificar eventos disruptivos e automaticamente reagendar o cronograma de chegadas, baseado em informações coletadas de tecnologias inteligentes no terminal portuário e nos membros do seu sistema logístico	Artigo 1
3. Desenvolvimento computacional e aplicação do método	Modelagem computacional e Simulação	iv. Comparar, por meio de Simulação de Eventos Discretos, indicadores de desempenho logístico operacionais e estratégicos do atendimento de caminhões em diferentes cenários, considerando atendimento estático e dinâmico.	Artigo 2

Fonte: Elaborado pelo autor (2022).

A partir da relação mostrada no Quadro 1, a descrição de cada etapa deste trabalho é apresentada a seguir, visando demonstrar o caráter científico da pesquisa.

a) Análise e Revisão da Literatura – essa etapa visa fazer uma revisão da literatura existente a respeito dos temas compreendidos neste estudo. Dessa forma, a Revisão Sistemática da Literatura (RSL) desta pesquisa está dividida em dois temas: Portos Inteligentes e suas tecnologias; e, métodos flexíveis de agendamento de chegadas. Essa divisão tem o intuito de considerar métodos flexíveis fora do contexto portuário que possam ser adaptados para a realidade deste estudo. Ainda, essa revisão da literatura está estruturada com base no método *Preferred Reporting Items for Systematic Review and Meta-Analysis* (PRISMA), descrito em detalhes por Moher *et al*. (2010). Ao final da RSL, têm-se o intuito de definir um conceito para Portos Inteligentes, selecionar tecnologias inteligentes com melhores resultados para a redução de congestionamento na hinterlândia portuária e identificar métodos de agendamento de chegada com flexibilidade e possibilidade de adaptação para o contexto portuário.

b) Desenvolvimento conceitual – a partir dos resultados obtidos com a realização da etapa anterior, foi desenvolvido um modelo conceitual para a construção de um método de agendamento de chegadas flexível, baseado no uso de tecnologias inteligentes no terminal portuário e pelos membros do sistema logístico. A estrutura deste modelo é demonstrada a partir de um fluxograma detalhado da interação entre as tecnologias, os membros do sistema logístico e o TAS.

c) Desenvolvimento computacional e aplicação do método – nesta etapa o modelo conceitual construído foi traduzido em uma linguagem computacional. Essa tradução ocorreu na linguagem de programação do *software* R® (R CORE TEAM, 2018), que possui a vantagem de ser *open source*, possibilitando um maior acesso e disseminação do código de programação. A partir de dados coletados em um terminal portuário brasileiro, o *software* realiza uma leitura das informações oriundas de tecnologias inteligentes, como localização em tempo real dos caminhões, e propõe reagendamentos para os atendimentos do *gate* de entrada, de maneira balanceada e adaptável a eventos inesperados. Assim, com a reprodução da simulação em diferentes cenários, foi possível comparar os resultados das abordagens flexível e estática, a partir dos *Key Performance Indicator* (KPI) definidos.

d) Disseminação dos resultados – esta etapa tem o intuito de disseminar os resultados obtidos no estudo e garantir a reprodutibilidade do método proposto. Para alcançar esse objetivo, foi realizada a confecção de dois artigos, sendo o primeiro relativo às revisões de literatura, performadas na etapa 1 e a construção do modelo conceitual, resultante da etapa 2; e o segundo baseado no desenvolvimento computacional do método, aplicação da metodologia em um caso teste e análise dos resultados obtidos. A combinação destes artigos resultou na estruturação dos pilares para esta dissertação.

3.2 ABORDAGEM PROPOSTA

O presente estudo pode ser caracterizado como uma pesquisa de modelagem quantitativa e simulação, que é definida por Bertrand e Fansoo (2002, p. 242, tradução nossa) como "pesquisas onde modelos de relações causais entre variáveis de controle e variáveis de desempenho são desenvolvidos, analisados ou testados". Os cenários avaliados neste estudo serão três: (i) cenário estático - operação do TAS em um terminal portuário brasileiro, sem a possibilidade de flexibilidade e adaptação; (ii) cenário com agendamento estático e tecnológico – operação de um TAS estático, mas com a utilização de tecnologias inteligentes para automatizar as operações portuárias, incluindo uma área de suporte logístico para pré-operação de caminhões com chegada fora de janela; e, (iii) cenário dinâmico e tecnológico - combinação de tecnologias inteligentes para o monitoramento e reagendamento do TAS frente a eventos disruptivos e o uso da área de suporte logístico para atendimento de caminhões com reagendamento não compatível com o horário de chegada.

Tendo em vista os cenários do estudo, a abordagem de Simulação de Eventos Discretos será empregada para a modelagem. A utilização de DES é justificada pela sua capacidade de avaliar mudanças no sistema, além de ser um método com aplicações bem-sucedidas na área de controle de agendamento de chegadas (LAW, 2007; KELTON, SMITH, STURROCK, 2011). Ademais, os estudos analisados para a revisão de literatura apontam para a eficiência de DES em estudos de *schedule* flexível, conforme pode ser observado na Seção 4.3.2.3 deste estudo.

Ainda, visando construir uma abordagem dinâmica e flexível para o funcionamento do TAS, selecionou-se a abordagem de *Machine Learning*, mais especificamente *Decision Tree*, para a predição da condição dos caminhões em tempo real durante o deslocamento do ponto de origem até o terminal portuário. O tópico 4.3.2.3.1 detalha o processo de escolha da abordagem de *Machine Learning* e esclarece o funcionamento do método.

Dessa forma, os cenários (i) e (ii) podem ser simulados com DES, enquanto o cenário (iii) exige a combinação de *Machine Learning* e DES, já que o modelo a ser desenvolvido necessita de um complemento para identificar os caminhões que precisam de reagendamento, a partir do monitoramento das informações dos membros do sistema logístico portuário. Ainda, conforme apresentado na Seção 1.2.1, o objetivo geral deste estudo está baseado na medição de indicadores de desempenho logístico do sistema portuário, onde foram definidos os seguintes indicadores:

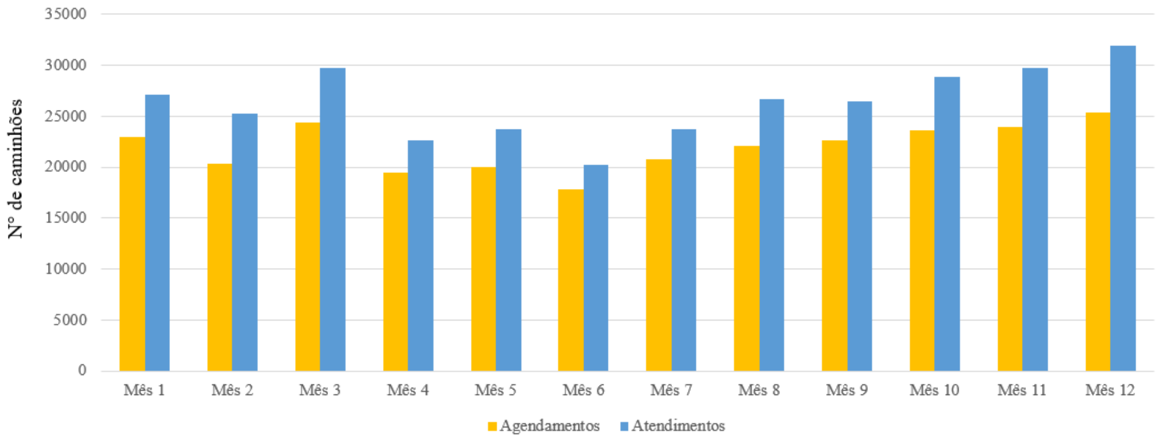
a) número médio e máximo de caminhões em fila no *gate* portuário – esse indicador permite analisar diretamente o impacto da inserção de tecnologias no ambiente portuário (cenário ii) e do método dinâmico de atendimento (cenário iii) para a redução do número de caminhões em fila na hinterlândia portuária. Ainda, a partir do resultado desse indicador é possível inferir se o método desenvolvido trouxe benefícios em relação ao trânsito na área portuária, já que este é um dos principais desafios enfrentados pelos gerentes portuários atualmente;
b) tempo médio e máximo de caminhões em fila – esse indicador tem o intuito de verificar se o uso de tecnologias (cenário ii) e o método dinâmico de atendimento (cenário iii) possibilitam uma sincronização dos participantes do sistema logístico portuário, reduzindo o tempo de espera nos *gates* portuários em relação a um ambiente de atendimento estático e sem tecnologias (cenário i);
c) quantidade de caminhões atendidos fora da data agendada inicialmente – esse indicador possui um caráter mais gerencial em relação aos apresentados anteriormente, já que possibilita uma análise da eficiência do TAS estático (cenários i e ii), em relação ao número de caminhões agendados e não atendidos e/ou atendidos fora do horário agendado, e do TAS dinâmico (cenário iii) com a possibilidade de reagendamentos em tempo real.

Dessa forma, a análise dos indicadores apresentados para a simulação dos três cenários propostos neste estudo permite a comparação entre os modelos de atendimento e identificação do impacto da utilização de um TAS flexível combinado com tecnologias inteligentes no desempenho logístico do sistema portuário. Ademais, a simulação do cenário ii, com um modelo de atendimento estático, mas com tecnologias inteligentes para automação das operações portuárias também permite uma análise em relação ao impacto apenas de tecnologias inteligentes nos indicadores analisados, enquanto o cenário iii se propõe a analisar o impacto da combinação de tecnologias inteligentes com um método dinâmico de atendimento, fornecendo, portanto, uma análise sistêmica para a tomada de decisão quanto a melhor forma de controlar o fluxo de caminhões na hinterlândia portuária.

3.3 APRESENTAÇÃO DO CASO TESTE

O método proposto neste estudo é baseado em dados históricos de um terminal de cargas conteinerizadas localizado no estado de Santa Catarina, região sul do Brasil. As informações utilizadas para o estudo de caso do método desenvolvido consistem em dados históricos de um período de 20 meses, entre janeiro de 2020 e agosto de 2021, coletados junto ao terminal parceiro. Visando evitar a interferência de sazonalidade no funcionamento das operações portuárias do terminal, selecionou-se um período de doze meses para a Simulação Computacional dos cenários propostos. O número de veículos atendidos nos *gates* portuários no período de doze meses analisados é exibido na Figura 3 e a Tabela 1 apresenta o número de atendimentos por mês no período analisado para as chegadas de caminhões na janela, adiantados, atrasados e não agendados.

Figura 3 - Dados históricos de agendamentos e atendimentos no terminal de estudo



Fonte: Elaborado pelo autor (2022).

Tabela 1 - Dados históricos da condição de chegada dos caminhões

Período	Na Janela	Antecipado	Atrasado	Não agendado
Mês 1	15.457	5.784	1.758	4.124
Mês 2	13.561	5.218	1.538	4.952
Mês 3	16.165	6.480	1.764	5.292
Mês 4	13.413	5.087	920	3.195
Mês 5	13.570	5.211	1.183	3.721
Mês 6	11.515	3.747	2.569	2.384
Mês 7	13.009	4.292	3.466	2.949
Mês 8	13.288	4.556	4.235	4.629
Mês 9	13.790	4.978	3.828	3.897
Mês 10	13.848	5.377	4.412	5.252
Mês 11	14.015	5.113	4.774	5.869
Mês 12	14.018	5.412	5.996	6.473
Total	**165.649**	**61.255**	**36.443**	**52.737**
Total %	**52,41%**	**19,38%**	**11,53%**	**16,68%**

Fonte: Elaborado pelo autor (2022).

Ainda, o algoritmo de *Machine Learning* usou aproximadamente 250 mil dados de atendimento para treinamento. As informações usadas para o funcionamento do algoritmo são referentes ao tempo estimado de viagem até o terminal em intervalos de 1 hora a partir do momento que faltam 4 horas para o horário de atendimento agendado. Informações detalhadas dos dados coletados e do funcionamento do algoritmo são apresentados na Seção 5.

4 DESIGN OF FLEXIBLE TRUCK APPOINTMENT SYSTEM BASED ON MACHINE LEARNING APPROACH

Este artigo foi aceito para publicação na revista International Journal of Logistics Systems and Management e será publicado em 2022.

Abstract

Smart Ports are adopting Industry 4.0 concepts and technologies so that more efficient and resilient operations emerge. Real-time data acquired from smart technologies can be deployed to anticipate disruptions and to actively manage hinterland - port flows. In this context, the flexible rescheduling of truck flows in response to unpredictable circumstances allows for congestion mitigation and reduced cycle time. This paper investigates the literature regarding Smart Ports, scheduling methods, and Machine Learning approaches, in order to propose a conceptual model for flexible Truck Appointment Systems, able to consider a continuous stream of real-time data from smart technologies to identify disruptive events and to dynamically reschedule truck appointments, ensuring the synchronization of hinterland - port truck flows.

Keywords: Smart Ports; Smart Logistics System; Truck Appointment System; Flexible Schedule; Machine Learning.

4.1 INTRODUCTION

The emerging integration of the world economy and the growth of international trade between countries from different continents in recent decades has provided an increase in opportunities for developing countries. Consequently, the demand in port terminals is intensifying along the years, and also a more competitive environment between port terminals has emerged (Chen, Huang, et al., 2019; Molavi, Lim and Race, 2020; Ruslan, 2021). Besides, there has been a change in the role of ports, in which the port terminals have started to be considered as the main actor capable of coordinate and create value for stakeholders in port logistics systems (Song and Parola, 2015).

Considering the role of port terminals and the increasing demand, technologies can connect data from different logistics stakeholders, create a synchronized system and also improve the infrastructure use (Cao et al. 2019; Lee et al. 2020). According to Triska, Frazzon, and Silva (2020), inland access of port terminals requires studies of capacity assessment and expansion planning to improve strategic decisions. In this context, one of the main challenges presented by Yau et al. (2020) for the port authorities is successfully controlling truck flows in order to reduce congestion and unnecessary waiting.

Molavi et al. (2020) points out that this challenging scenario, where ports need to develop solutions to cope with current demand and maintain a long-term planning, is contributing for the transformation of modern traditional ports into Smart Ports. In the definition of Yang et al. (2018), Smart Ports can be described as an integration of smart sensors and actuators, wireless devices, and a system with centralized data, in which the port terminal operates fully automated and allows port authorities to be more resilient and to provide efficient services based on real-time information.

Examples of port terminals implementing smart technologies in their operations are the ports of Rotterdam, Hamburg, and Singapore (see, e.g., Durán, Córdova, and Palominos (2019) for more details). Alop (2019) states a significant reduction in truck congestion at port hinterland with the adoption of these technologies. This statement allows us to infer that synchronization of real-time data between members of port logistic system increases the control of trucks arrival time, reducing the congestion at port gates, ensuring a reliable process.

However, Frazzon et al. (2019) warn that only the adoption of smart technologies is not enough to solve the operational problems of ports, especially due to the increase in demand. They propose the application of advanced planning, truck schedule and a real-time monitoring of vehicles flow with destination to port areas. In this direction, Truck Appointment Systems (TAS) is a successful approach applied to reduce congestion and waiting times at ports, in which trucks are allocated to specific time windows, enabling port terminals to be aware of the estimated truck flow (Li et al., 2020; Mar-Ortiz, Castillo-García and Gracia, 2020).

Despite the benefits of TAS utilization, the existence of a non-flexible system, which does not consider disruptive events, can lead to conflicts between port authorities and cargo transport companies, so that a future generation of Truck Appointment Systems must allow for the flexible rescheduling of flows in response to unpredictable circumstances.

Recently, uncertain scenarios, as the COVID-19 pandemic further increased the need for flexibility in global supply chains and logistic systems, highlighting the importance of adaptable services with high response capacity (Dente and Hashimoto, 2020; Shokrani et al., 2020). Adobor (2020) suggests that to obtain resilience, the logistics systems should operate dynamically and allow adaptation.

To design a flexible TAS, deploying data acquired from smart technologies to synchronize hinterland - port area truck flows for reducing congestion and unnecessary waiting is among the most promising opportunities in this subject field. According to Johnson, A., Johnson M. and Nagarur (2021), in the literature, different approaches are being employed to design systems to operate under disruptive scenarios, with strategies for based on robustness and resiliency, such as flexible systems, in which the Machine Learning (ML) approach, used by Balster et al. (2020) to predict Estimated Time of Arrival (ETA) for intermodal freight network involving port terminals, combining data from different actors in the port logistics system, can be cited as an example.

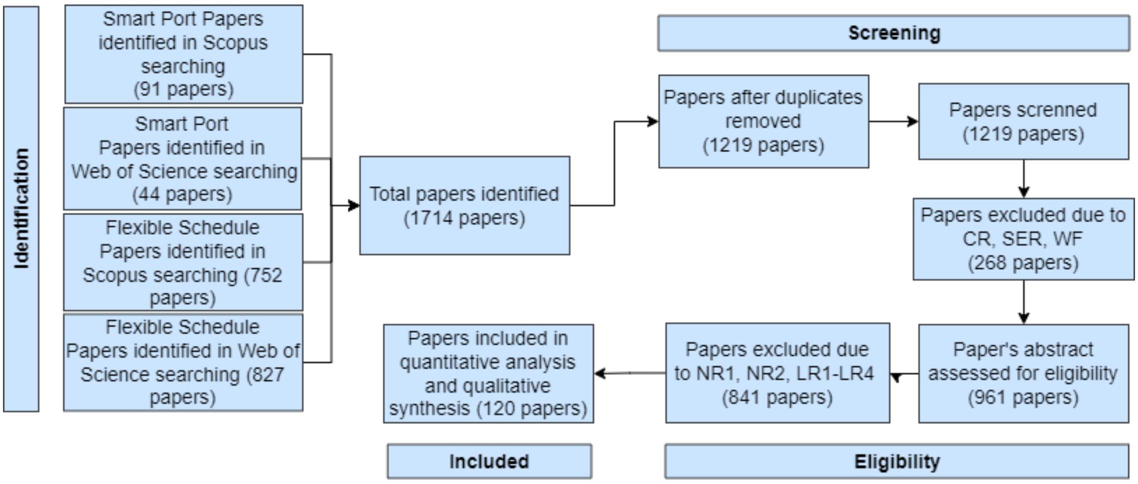
Based on the challenging scenario of port systems described above, the aim of this paper is to design a conceptual model of flexible Truck Appointment System integrating data from smart technologies to identify disruptive events and dynamically reschedule the appointments, avoiding delays and controlling the truck flow at port hinterland. In order to achieve this objective, this paper review the literature regarding Smart Ports and flexible scheduling methods, especially Machine Learning approaches. The proposed model can deal with a continuous flow of data from smart technologies to identify disruptive events and dynamically reschedule truck appointments.

The remainder of this paper is structured as follows. In Section 2, the methodology used to construct this paper is shown. In Section 3, the results from quantitative and qualitative analysis regarding the literature review are presented. Section 4 details and discusses a conceptual model for flexible truck schedule in Smart Ports. Finally, in Section 5 the conclusions are given, and future research directions are pointed.

4.2 RESEARCH METHODOLOGY

The research methodology used in this paper consists in a systematic literature review to support the design of a conceptual model for flexible TAS. We based our review in the Preferred Reporting Items for Systematic review and Meta-Analysis (PRISMA) method, described in detail by Moher et al. (2010). Figure 1 illustrates the steps performed to construct this research.

Figure 1 PRISMA steps demonstrating the phases of this review.



4.2.1 PAPERS IDENTIFICATION

As mentioned in the above section, we are integrating Smart Ports and flexible schedule in our research and in order to perform a detailed literature analysis, we divided our systematic review into two parts: the first one to collect information regarding Smart Port concept and technologies, and the second to identify flexible schedule methods, also including Machine Learning approaches, in distinct environments, which has the purpose to expand the search for methods outside the maritime sector, but only considering applications that can be implemented in this area. Thus, we start our research collecting papers in reputed databases, which covers the main journals in the research area: Scopus and Web of Science.

The search string for Smart Ports was constructed as follows: TITLE-ABS-KEY ("smart port*" OR "port 4.0" OR "smart supply chain*" OR "smart port hinterland"), while the string for flexible schedule was: TITLE-ABS-KEY ((“flexib*” OR “adaptab*” OR “machine learning”) AND (“schedul*” OR “appoint*”) AND (“truck*” OR “vehicle*” OR “arrival*”)). Both researches were limited to articles as document type and English as language. Furthermore, in the research about flexible schedule methods, we review the subject areas and consider only papers published in areas that allows reproduction of the method in the port sector, which can be seen in the Specific Area (SA) criteria, presented in Table 1.

4.2.2 PAPERS SCREENING AND ELIGIBILITY

The second part of the methodology used in this review is focused on screening the articles. So, we removed duplicated papers using the software R Studio, which also was employed to perform a bibliometric analysis with the bibliometrix package, developed by Aria and Cuccurullo (2017). Moreover, Table 1 shows the criteria adopted to exclude papers, adapting the rules followed by Uhlmann and Frazzon (2018). In the first phase of our screening, we exclude papers classified as SER, WF, NR1 and SA.

Table 1 Screening criteria

Principle	*Criteria*	*Description*
Inclusion	Closely related (CR)	The research content is explicitly dedicated to smart port or flexible schedule methods; Document type: Article; Language: English; Time span: before the end of February/21.
Exclusion	Search engine reason (SER)	Only a part of the paper is available in English, but not the full text
	Without full text (WF)	The full text of a paper is not available
	Non-related (NR)	NR1: Papers that are not academic article; NR2: Papers not in line with “smart port” OR “flexible schedule” theme.
	Specific Area (SA)	Flexible schedule is used only for a specific area: we maintained only papers applied in engineering, computer science, decision sciences, mathematics, medicine, materials science, operations research management and transportation science that allow the method to be reproduced in the port area.
	Loosely related (LR)	LR1: Smart port or flexible schedule is only used as an example; LR2: Smart port or flexible schedule is used only to point future research opportunities; LR3: Smart port or flexible schedule is used as a cited expression; LR4: Smart port or flexible schedule is used only in keywords and/or references;

Successively, we read details, such as title, abstract and keywords of the selected articles and exclude articles classified as NR2 and LR1-LR4. Finally, we read the full content of papers included in our final portfolio. Still, with the selected group of papers, we perform quantitative and qualitative analysis, which we present the results in next session.

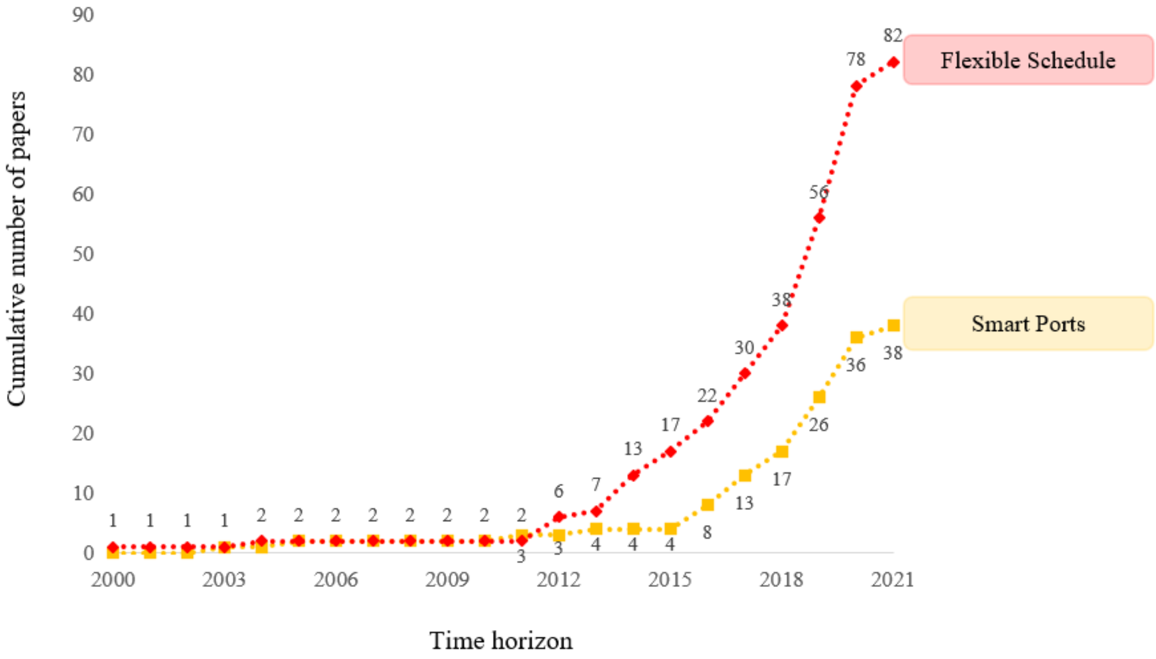
4.3 RESULTS

On the one hand, the quantitative analysis aims to identify patterns and understand the emphasis of researches in the studied topics. On the other hand, the qualitative analysis focus on in-depth analysis to extract information and support the design of a flexible TAS.

4.3.1 QUANTITATIVE ANALYSIS

Based on the methodology employed, 120 papers were included in the quantitative analysis, in which 38 addresses smart port context and 82 focuses on flexible schedule methods. Figure 2 presents an evolutionary analysis regarding the accumulated number of papers published over the years in both topics that are included in our review

Figure 2 Scientific publications in the research area over time



First, the analysis of publications in the time horizon allows us to affirm that both subjects are relatively new, with the first paper published found in 2000 and are being more studied in the last few years. In this sense, we can see a more considerable increase in the number of publications per year since 2015, in which from that year there are at least four papers published about smart ports and five papers published about flexible schedule per year. In 2020, it was reached the maximum number of papers published in the same year, with 12 and 22 papers published about smart ports and flexible schedule, respectively. Until the date of our review, we identify two papers addressing smart ports and four papers related to flexible schedule published in 2021. So, we can affirm that there is a tendency of increase in the potential of this area due to the diffusion of benefits from using smart technologies in ports, as well as flexible schedule methods, highlighted by the COVID-19 scenario, in which logistics systems are required to be more resilient and flexible, identifying disruptive events and dynamically providing rescheduling.

We also conduct a bibliometric analysis to identify relevant information from the keywords used by the authors to classify their papers. Figure 3 and 4 shows the word growth over the years for the five most cited keywords in the researches addressing smart ports and flexible schedule methods, respectively. Related to smart ports, the most used keyword is ‘smart port’, evidencing mainly that authors are still focused on proposing definitions and identifying the characteristics of smart ports. In addition, we can see that some researchers are expanding the analysis of intelligence to a port supply chain or port logistics system visualisation, aiming to define and conceptualise the requirements to synchronise data in an intelligent platform shared between the port logistics system.

Figure 3 Word growth for the keywords in the researches addressing smart ports

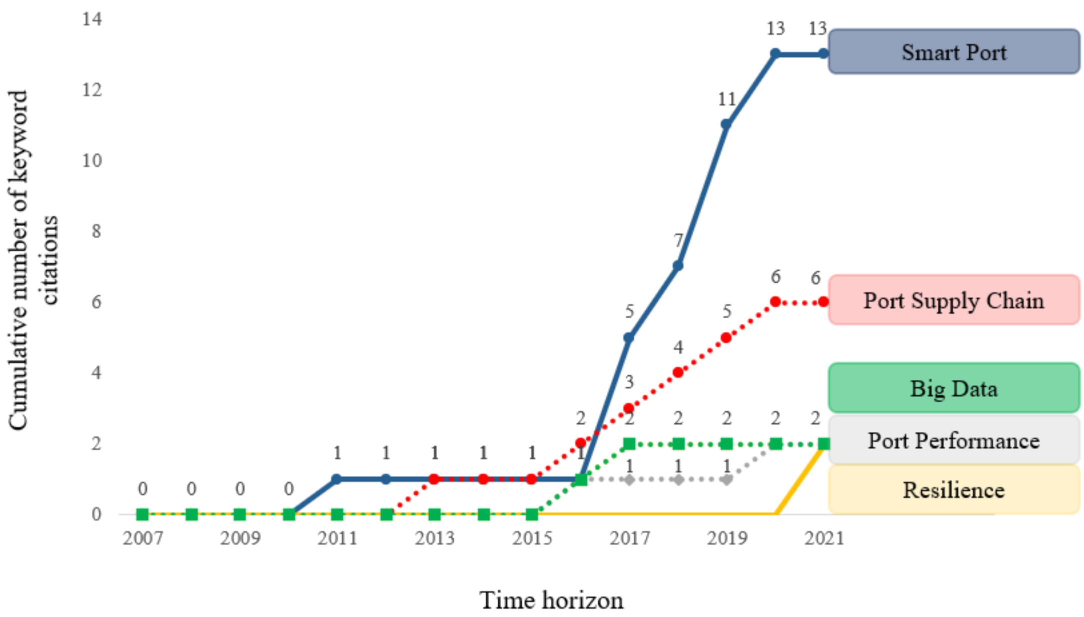
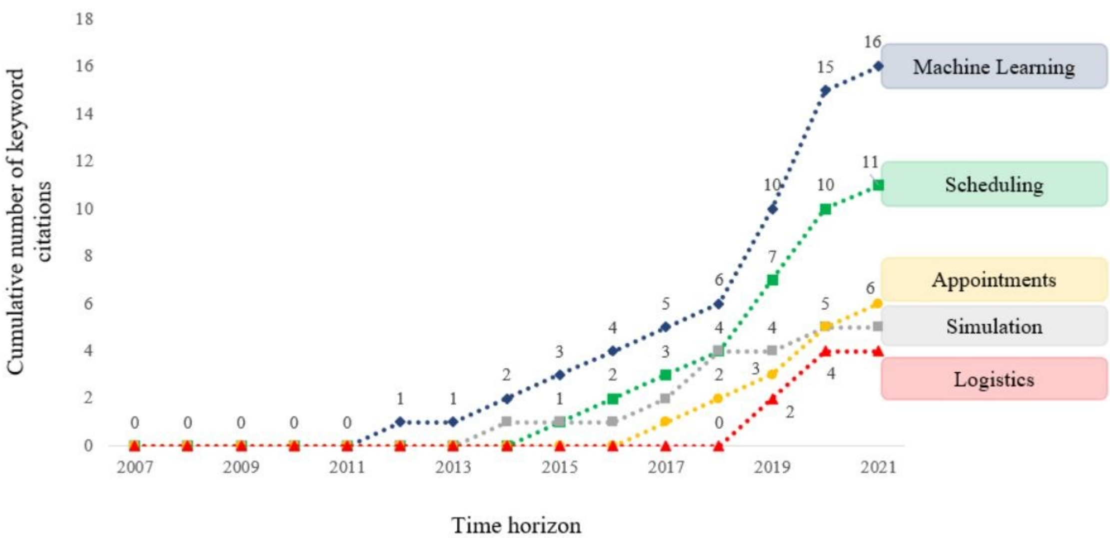


Figure 4 Word growth for the keywords in the researches addressing flexible schedule



Meanwhile, the articles related to flexible schedule methods demonstrate that since 2012 the authors are proposing ML approaches to design flexible schedules, with a considerable increase in developed studies annually since 2018. The increase in the number of articles applying ML allows us to infer that the results of the first studies developed influenced the diffusion of this approach to different areas along the years. Besides, studies relating appointments to flexible schedule methods started to be developed only in 2016, and are still in the infancy phase of study, charactering a promising opportunity of research, especially in the actual global logistics scenario. The keyword 'simulation' demonstrates that computational experiments are a common technique used by authors to test and validate their methods. In addition, keywords as 'scheduling' and 'logistics' are mainly used to classify the studied field of the articles.

Combining both analyses, we can better visualise the research opportunities and the correlation between smart port and flexible schedule methods. In this sense, in the scope of our research and based on the quantitative analysis performed, the subjects are connected since the smart technologies enable the extraction of real-time data, that can be used to design a flexible TAS, in which rescheduling is dynamically proposed in response to the identification of unpredicted circumstances.

4.3.2 QUALITATIVE ANALYSIS

The qualitative analysis performed in this research have the objective to answer three main questions:

(1) What is the concept adopted to describe a Smart Port?

(2) Which technologies are being used in Smart Ports?

(3) Which methods are being employed, in different environments, to design flexible schedule?

4.3.2.1 Smart port concept

Traditionally, ports are considered integrated centres for logistical information on global logistics system, operating under international business transactions and complex infrastructure (Molavi et al., 2020b). However, the definitions of functionalities and maturity level of ports have been changing over the years in a classification of six generations. The first three generations, considering the model proposed by the United Nations Conference on Trade and Development (UNCTAD), are more concerned about port services and operations (Chen et al., 2019), where in the first generation, the port can be characterised as a simple nodal point connecting deliveries in the supply chain; the second generation aggregates the use of robust infrastructure and more equipment in port operations; and in the third generation, ports start to play the role of warehousing, packaging and distribution centre (Yau et al., 2020).

According to Chen et al. (2019), the fourth generation of ports adds the functionality of central point in coordination and integration of port logistics system members to the port terminal and the fifth generation emphasises the use of technologies to provide information and allow port managers to take decision based in real-time monitoring, characterising the concept of Smart Ports. Moreover, the sixth generation, which still is in an initial stage of definition and study, considers that by the year of 2050, ports must have "[…] modern storage methods, automating terminals, developing and implementing innovations in the field of technological and organisational" [Karaś, (2020), p.28].

Ports that reach fifth generation maturity level often are called smart ports, but it is also possible to find mentions in the literature as intelligent ports, digital ports, robotic ports, or even, autonomous ports (Jun et al., 2018). From this non-consensus nomenclature definition, Molavi et al. (2020b, p.3) describes the fifth generation of ports as 'a connected port that combines broadband communications infrastructure, flexible and service-oriented computing infrastructure, and innovative services to meet demands.' Additionally, the smart port concept is correlated to the Industrial Revolution 4.0 and so, the integration of information and communication, the use of digitalisation and the information-oriented industry are key criteria in the idea of smart (Salleh et al., 2021).

Regarding characteristics of a smart port, González et al. (2020) associate this nomenclature to the use of technologies to obtain interactivity and dynamism to port services, making the operations more reliable. Furthermore, the concept of smart port can be connected to port sustainability through management decisions that prioritise the use of sustainable technologies, reducing the negative impact of port operations in the environment and involving port stakeholders in the sustainability strategy (Ashrafi et al., 2020; González et al., 2020).

Jun et al. (2018) adds to the smart port characteristics the use of automation in the operations in order to achieve high productivity. Chen et al. (2019) defines smart port as maritime terminals that adopt intelligent systems in operational activities, coordination of logistics system members, financial and trade information control aiming to construct an environment with systematic, strategical, efficient, and more flexible decisions interconnected with stakeholders.

Regarding this exchange of information, Kamolov and Park (2019) consider that a Smart Port must be equipped with technologies that allow real-time communication with vessels, other ports and transport members, as truck companies, in order to monitor and control the location of cargos and update schedules. Additionally, Yang et al. (2018) suggest that the smart port definition is based on the use of modern and automated infrastructure to share information with stakeholders via wireless to obtain faster and more efficient services.

In this sense, smart ports involve intelligent technologies to operate with maximum automation and provide precise data for port authorities make decisions with modern and efficient methods (Alop, 2019). The management of smart ports is also discussed by Karaś (2020), which defines the concept as a model of management integrated with technological processes. Besides the technological perspective, the smart port concept is frequently associated with environmental questions, sustainable energies, cybersecurity, social aspects and strategic management (Jia and Cui, 2021; Usman and Gutierrez, 2018; González et al., 2020; Munim et al., 2020).

Frazzon et al. (2019) broaden the smart port concept to a smart port-hinterland concept, suggesting that an efficient and reliable performance of port operations is dependent of synchronisation in port logistics system member's activities to respond quickly to external disturbances. Furthermore, the adoption of intelligence in port terminals can be assigned as a part of Smart City systems, considering that ports and cities are intrinsically connected, and port activities influence directly on urban areas from the cities (Chen and Lam, 2018; Yau et al., 2020). In these directions, smart ports act as an important actor in the smart logistics systems, tracking, monitoring, managing traffic in port hinterlands and providing socio-economic benefits to cities and regions (Yau et al., 2020).

In this paper, we consider smart port as a modern terminal that combines automation with flexible services integrated to the entire port logistics system through real-time communication from smart technologies, allowing more resilient, efficient, sustainable, and reliable strategic decision to port managers, providing benefits to stakeholders and urban areas impacted by port activities. In reference to technologies adopted in Smart Ports, in the next topic we present the most cited technologies employed in port terminals by the authors included in our review.

4.3.2.2 Smart technologies in port hinterlands

Smart technologies are being adopted in modern port terminals with the aim to improve operations in the maritime industry and provide integrated and updated information (Salleh et al., 2021). We reviewed 38 papers addressing smart port to answer which technologies are being used in smart ports. To classify the most used technologies in the context of smart ports, we identified the number of analysed papers that relates the technology with the concept of smart.

So, the main technologies associated to the concept of smart ports are: internet of things (cited by 47% of the analysed papers), Big Data (47%), sensors (42%), automation (39%), radio-frequency identification (37%), wireless sensor network (29%), global positioning system (GPS) (26%), Wi-Fi (21%), mobile devices (18%), artificial intelligence (18%), video system (16%), and connection technologies (13%). Between the technologies pointed by the authors, we analysed the ones with more relation with the considered problem of this study and that can be used to synchronise the truck flow at port hinterland.

Regarding port gates, Heilig and Voß (2017) suggests a model of smart port operating with RFID and optical character recognition (OCR) at the entrance gate, which is also signalised by Min et al. (2017a). In this sense, the RFID record the location of trucks every time the truck passes an RFID station, while the OCR system perform as an automatic recognition of patters in scanned documents or images, providing more efficiency to operations realised in port gates, acting as a pre-gate or automatic gates for vehicles procedures check (Heilig and Voß, 2017). Besides, Yau et al. (2020) propose the use of detection devices, such as video cameras and face recognition systems for truck drivers control at port gates. These technologies can help to reduce the required time to attend each truck at the port gate and better control truck appointments.

Moreover, De la Peña Zarzuelo et al. (2020) relates the importance of automation in port terminals, highlighting that the use of automated systems and equipment enable more reliability, resilience, and efficiency to operations. In port gates, automation can be employed to optimise the processing time of each truck during the entrance process, which directly influences to reduce the congestion, and provide a system with less dependence of human intervention, minimising errors.

Molavi et al. (2020b) instruct that GPS is implemented in many intelligent infrastructures of systems, to share real-time location between port logistics system members. Examples can be seen in the OnTrack application, developed by the Port of Rotterdam, and the port-IO system, designed by researchers from the University of Hamburg. The OnTrack provide expected time of arrival for trains in the terminal and predict the schedule of processing times (Karaś, 2020), while the port-IO works in a mobile app, accessed directly from truck driver's smartphone, and aims to reprogram truck routes and avoid wasting time during the transport (Heilig et al., 2017).

Related to the use of smart sensors and IoT, the sensors collect data from different operations, while the IoT technology refers to the connection and exchange of data between sensors, objects, and systems, enabling intelligent decisions and the forecasting of conditions (Ferretti and Schiavone, 2016; Jun et al., 2018). However, Fernández et al. (2018) warns that the use of sensors and smart technologies involve a massive volume of data collected, which requires proper treatment. Big Data is the most efficient technology to manage large storage space of data (Min et al., 2017b). As smart ports are characterised by the dynamic exchange of data between sensors, objects and systems, Big Data is a necessary technology to manage the integrated data.

Furthermore, Kamolov and Park (2019) points out the importance of connection technologies, such as 3G/4G/5G or even Wi-Fi, to enable communication between devices anytime and anyplace, and consequently update the port system in real-time. Thus, connection technologies can be used to connect devices inside the port area, as sensors and systems to exchange data, and between different actors in the port logistics system, as truck drivers and the port system. By this integration of data in real-time, the port system can be more prepared to quickly adapt and respond to unexpected circumstances.

Besides, the integration of data between port logistic systems is proved to improve the performance of port terminals, as shown in Han (2021) that found a significant impact of customer integration in the quality performance of port terminals. Ivanov et al. (2021) point out that digital technology integrates information from the supply chain and provides resilience, avoiding unexpected disruptions. Richey and Davis-Sramek (2021) claim that the COVID-19 pandemic accelerated the connection process and the adoption of technologies in global supply chains. So, methods to reduce uncertainty regarding operational decisions and identifying disruptions proactively can bring benefits to the actors in the logistics chain and prevent potentially severe consequences to the supply chain (Nur et al., 2020; Bodé et al., 2021).

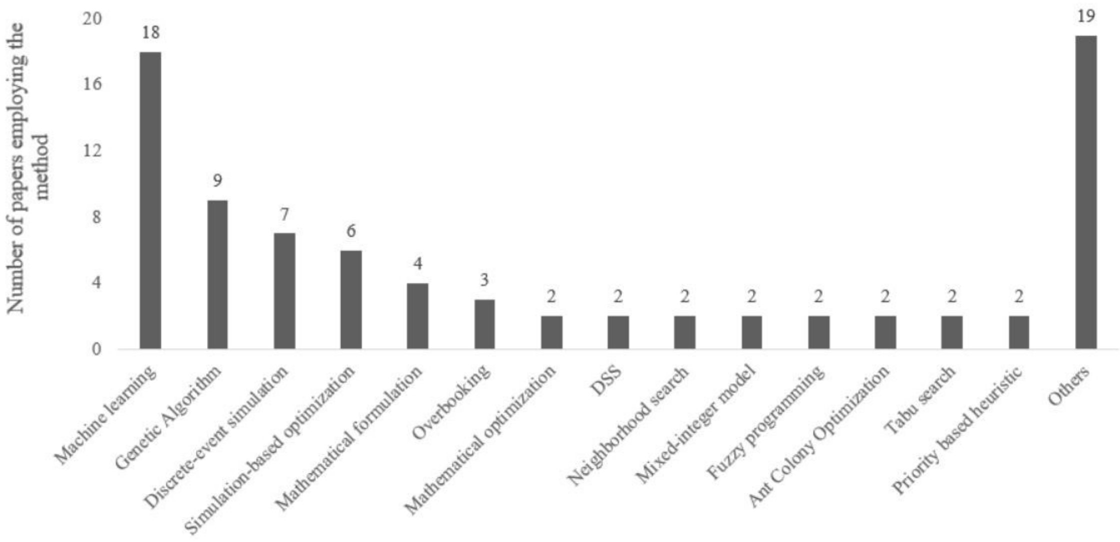
Therefore, there are many other smart technologies that can be used in the context of smart ports and as mentioned by Karaś (2020), the definition of the adopted technologies is related to specific factors of each port terminal, as the type of cargo handled. In the context of the scenario studied in this paper, in which smart technologies are used to design a flexible TAS, we identify that the main technologies capable of reducing truck congestion and synchronise data between port logistics system members are: internet of things, Big Data, smart sensors, automation, GPS, radio-frequency identification, mobile devices, video system, OCR, connection technologies, and check-in gates.

4.3.2.3 Flexible schedule methods

Scheduling methods can be characterised as an approach to optimise resources over time to perform sequential or parallel activities (Shukur et al., 2020). Static TAS is a common approach adopted in port terminals to define the exactly entry time of each truck, without allowing rescheduling (Chen et al., 2013). However, Leusin et al. (2018) emphasise the existence of problems caused from static schedule systems, which works considering certain premises and can be easily deteriorated with the introduction of uncertainties or non expected events. To solve this problem, new schedule methods considering real-time monitoring and reschedule to reduce the impact of disruption in the system, began to be more studied in the last few years (Van Lieshout et al., 2018).

An example can be seen in the study of vehicle routing problem with time windows (VRPTW) to reduce the number of vehicles and the total distance travelled (Silva Júnior and Leal, 2021). Also, the study of Mancini and Gansterer (2021) developed an approach to solve the vehicle scheduling problem with a weekly time-horizon and combination of potential customers and required tasks. Thus, aiming to understand the methods employed in different environments to design flexible schedule, we review 82 papers addressing this topic. Firstly, we categorise the papers between single-method and multi-method to analyse if the researchers are combining different methodologies to design flexible schedule, and we discovered that 83.75% of the papers apply single-method, which means that the majority of researches in this topic use only one method to design flexible schedule systems. Secondly, we identified the methods utilised by the authors, analysing the most used methods and how they are employed in each scenario, as can be seen in Figure 5.

Figure 5 Analysis of the methods used to design flexible schedule



Regarding the adopted methods, we investigated them and group the methods with only one citation in a category named ‘others’. The most cited methods to design flexible schedule are: ML (employed in 23% of the analysed papers), genetic algorithm (GA) (11%), discrete-event simulation (DES) (9%), simulation-based optimisation (8%), mathematical formulation (5%), and overbooking (4%). According to Chen et al. (2018), the overbooking technique consists of scheduling more appointments than the capacity of the system, based in the forecasting of delays and no-shows, but this technique can overload the system when all appointments show up without delay, causing congestion. In port terminals, the overbooking is applied in the context of TAS (Wasesa et al., 2021).

Another method identified, the mathematical formulation is the approach used to solve a problem from the analysis of mathematical equation, considering the variable related to the studied topic, as developed by Wisittipanich et al. (2019), which applied mathematical formulation to study truck scheduling in the cross-docking network to obtain synchronisation of truck schedule. In the context studied in this paper, mathematical formulation can be focused on developing dynamic rules to manage the appointments and propose reschedule. The disadvantage of mathematical formulation is that problems, such as scenarios with real-time monitoring are complex do model.

Also, simulation-based optimisation is described by Castilla-Rodríguez et al. (2020) as an approach that bases the simulation in an optimisation algorithm, in order to test the results of the provided solution by the algorithm performing a looping until the simulation results identify the optimal solution for the studied problem. In this sense, Liu et al. (2019) had already studied a flexible manufacturing system (FMS) problem and employed the simulation-based optimisation method to construct a flexible schedule of vehicles and machines.

Furthermore, Rodrigues et al. (2020) explains that the DES method is used to test experiments and evaluate the results of scenarios with entities and resources varying. To design a flexible schedule, DES can be applied to analyse dynamic operations, such as the variation of resources based in the number of appointments along the time or evaluate the behaviour of the system when unpredictable circumstances occur.

The GA is an evolutionary and meta-heuristic algorithm employed to optimise solutions and solve problems in different areas (Jafari-Marandi and Smith, 2017), and accordingly to Rey et al. (2014) is efficient to design re-scheduling strategies. Thus, a possibility of implementation of GA in the context of our study is to design the reschedule policy to the TAS, using real-time data from the port logistics system members to propose reschedule between previous appointments.

Finally, the most cited method by the reviewed papers is ML, which consists in techniques to identify conditions, e.g., traffic situation, and forecast future behaviours based on data from past events (Balster et al., 2020). The main reason for ML being the most cited method is due to its capacity to provide precise results since the algorithms are based on real-time learning and can quickly adapt and behaviour responsively in circumstances of disruptive events. Additionally, ML can be implemented as different approaches and to detail the individual applications, we discuss in the next topic the approaches identified in our review.

4.3.2.3.1 ML approaches

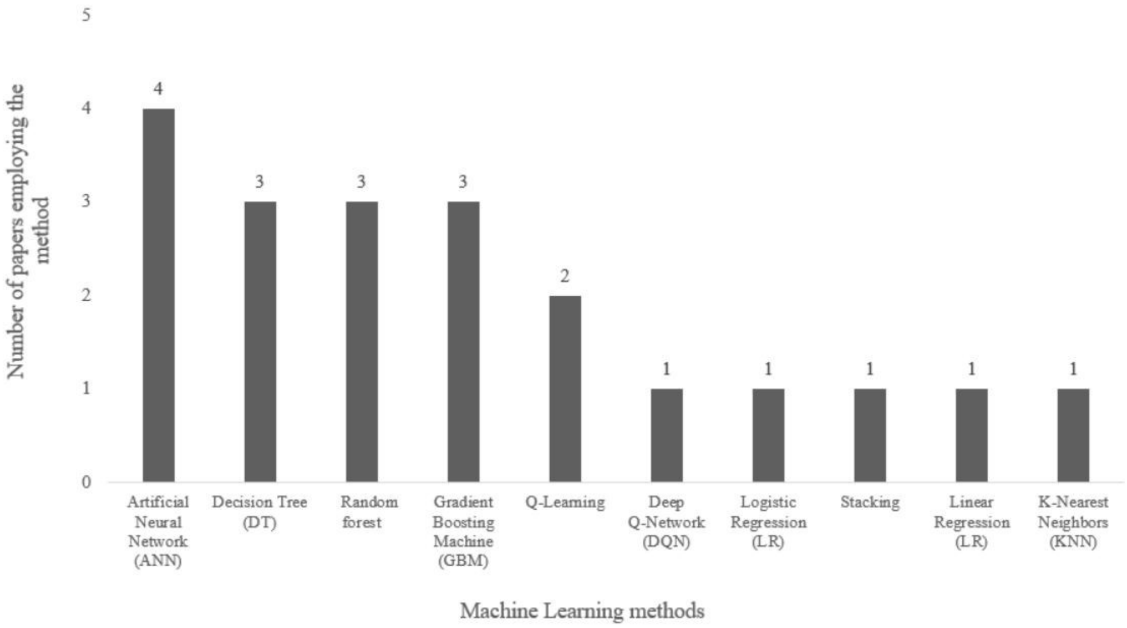
The ML approaches can be classified in five categories: supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning and transfer learning (Chinnamgari, 2019). Table 2 presents a summary of possible classification and example of approaches to each category, based on the studies of Ang et al. (2016) and Chinnamgari (2019).

Table 2 Machine Learning classification

Classification	*Description*	*Examples of approaches*
Supervised learning	Applied to discover the effects of pre-categorized data in the output of the system to achieve a clear objective.	Artificial Neural Network (ANN), Decision Tree (DT), K-Nearest Neighbour (KNN), Gradient Boosting Machine (GBM), Logistic Regression and Linear Regression.
Unsupervised learning	Used in unlabeled data with the main objective of identify similar behaviours and classify data into clusters.	Clustering.
Semi-supervised learning	The semi-supervised learning includes a small sample of labeled data to a group of unlabeled data to improve the algorithm performance.	Random Forest and Stacking.
Reinforcement learning	Used to develop algorithms without labeled data, but considering feedback received from decisions to guide future algorithm’s decisions.	Q-Learning and Deep Q-Network.
Transfer learning	Transfer learning algorithms adopt information obtained in similar scenarios to solve problems in circumstances without available data.	Convolutional Neural Networks for Visual Recognition.

As presented in Table 2, the main criteria to identify the most suitable ML approach to solve a problem are related to the available data and the main objective of the algorithm to be developed. In our review, we choose to consider studies from different environments, and so, we found application of approaches from distinct categories of ML methods. In addition, we analyse papers that apply distinct ML approaches to compare the results obtained by each approach, as can be seen in the paper of Alam et al. (2021). Figure 6 points out the adopted approaches by the reviewed studies.

Figure 6 Analysis of ML approaches adopted to design flexible schedule



As the available data of smart ports, such as real-time location, previous appointment time and gate operational time can be considered as labelled data with clear objective, we focus on the analysis of supervised learning approaches. So, analysing the results presented in Figure 6, we found 13 applications of supervised learning approach, being four of ANN, three of DT, three of GBM, one of logistic regression, one of linear regression and one of KNN.

KNN is described by Wang et al. (2020) as a nonlinear lazy learning algorithm based on regression analysis, in which the method consists in training the dataset from the interpolation of nearest neighbours. However, in the experiment performed by Wang et al. (2020) to predict ETA in a terminal manoeuvring area, KNN was considered the worst ML tested approach.

Linear regression is a model supported by mathematical functions to statistically predict unknown variables (Putra and Nasrudin, 2019). Withal, in a similar circumstance of KNN, when linear regression was compared to different approaches by Putra and Nasrudin (2019), the authors identified better results using other ML approaches to design flexible schedules.

Logistic regression is described by Bertsimas and King (2017) as a statistical approach implemented to group data when the available variables are binary. In the study of Srinivas and Ravindran (2018), the logistic regression approach performed better than ANN and GBM to optimise an appointment system for patients in a healthcare environment.

GBM is a model derived from tree-based algorithms, in which scenarios with missing data can be designed without negatively impact in the results of the experiments and the predictions are performed with gradient descent solutions (Wang et al., 2020). In one hand, the GBM method achieved the best performance between the supervised methods in the experiments of Wang et al. (2020) to predict ETA, and on the other hand, in the experiment of Srinivas and Ravindran (2018) the method performed worst than logistic regression and ANN.

DT is defined by Fiskin et al. (2021) as a flow-chart like tree form with simple visualisation, integrating nodes that represents different results for variables tested. Although we did not find papers in our review comparing the result of DT application with other supervised methods, the studies of Fiskin et al. (2021), and Lin and Fan (2019) points out several benefits of adopting this approach: the method has the ability to revel interactions between variables; the DT algorithms are capable of analyse complex data; and DT can be implemented to design models, describe patterns in data and support predictions. Also, the study of Guinness (2015) proved an accuracy of approximately 97% in the DT method to classify events.

Furthermore, ANN consists in the process of learning behaviours from the analysis of relationship between attributes, requiring a sample of data in advance to train the algorithms and optimise results in scenarios with difficulty to make data association (Kang et al., 2019; Putra and Nasrudin, 2019). ANN is the ML most cited method in the papers included in our review, mainly due to the method capacity to be consistent and solve complex problems achieving good performance on flexible schedule experiments, such as the researches of Alam et al. (2021) and Srinivas and Ravindran (2018).

Therefore, between the supervised ML approaches we reviewed, we identified logistic regression, DT and ANN as the most suitable methods to be employed to design a flexible TAS. However, comparing the similarities between the scenarios in which we found application of the approaches and our study, we considerer that DT has more advantages, since the method enables the design of rescheduling rules, where the real-time data from port logistic system members can be processed and categorised to quickly identify the existence of unexpected events, highlighting the status of each truck in the system and consequently, suggesting the rescheduling of appointments.

4.4 CONCEPTUAL MODEL AND DISCUSSION

As explained in previous section, the main aim of this study is to design a flexible TAS integrating data from smart technologies to identify disruptive events and dynamically reschedule the appointments, and so, based on the literature review performed, we divided our conceptual model in three parts: smart port operation, to explain how the technologies will be integrated to exchange data; rescheduling policies, to detail the adopted criteria for the functioning of the flexible schedule; and, the DT approach, explaining the details of the proposed method to solve this problem.

4.4.1 SMART PORT OPERATION

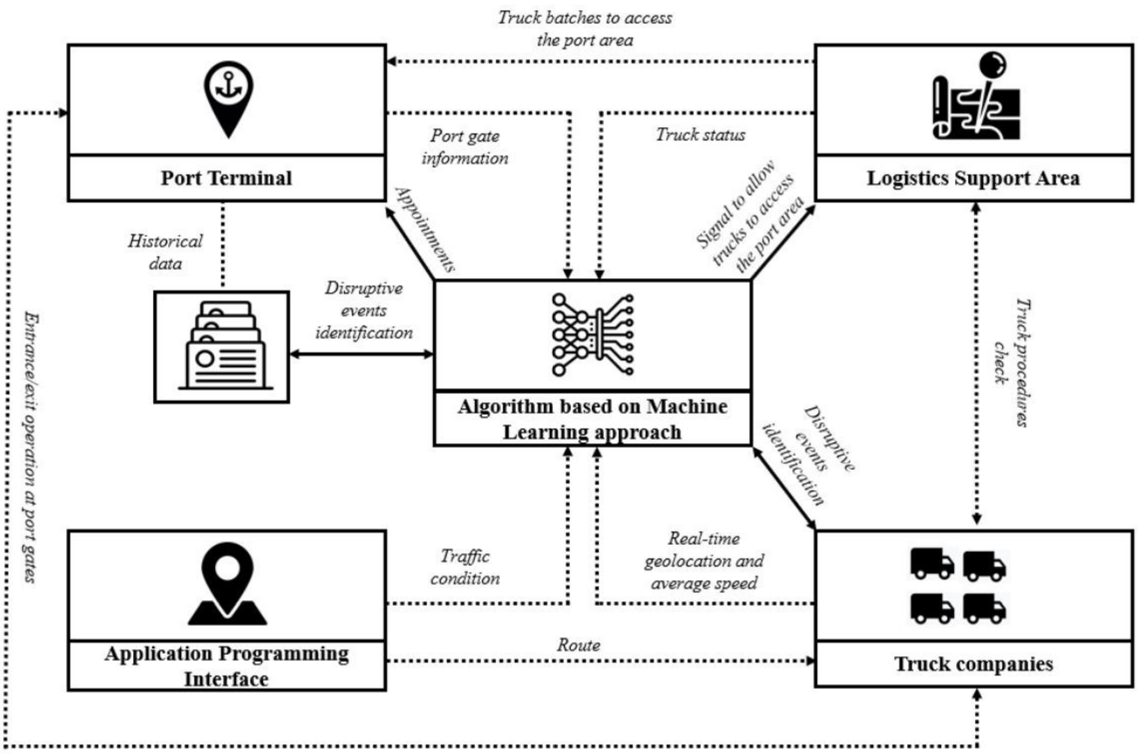
The model of smart port we consider in this paper, as described in previous section, consists in the use of IoT, Big Data, smart sensors, automation technologies, GPS, RFID, mobile devices, video system, OCR, connection technologies and check-in gates. In this sense, firstly, we consider the organisation of the daily truck appointments in a digital platform, in which the data from each truck, the truck drivers and the cargo to be transported is previous, registered. From this, the truck driver should access a digital application in a mobile smartphone before leaving from the origin point to the port terminal, and in this app, the real-time location of each truck and the speed will be collected and shared to the port terminal system using an application programming interface (API), such as Google Maps. Besides, RFID tags should be allocated in trucks to facilitate the exchange of data regarding truck location in specific places.

Furthermore, to completely avoid the existence of congestion at port terminals, we expanded the check-in gates suggestion to a logistic support area (LSA). Basically, the LSA consists in an area similar to a dry port, located in a maximum distance of 50 kilometres from the port terminal, directly connected to a highway and equipped with smart technologies, as RFID readers, OCR, video system control and connection technologies to operate as a truck procedures check. So, instead of trucks going directly to the port terminals, our Smart Port operation considers that trucks need to go first to the LSA, in which the truck information should be automatically compared to the registered data, allowing the update of information, when necessary, and then the truck should wait for a signal to access the port area. In this sense, this signal emission aims to control the truck flow at port hinterland, organising the access to port area in small truck batches considering the real-time status of port gates.

Finally, in port area, the access should be fully automated to minimise the existence of human errors, and so, smart sensors should be used to analyse the port gates status, such as the number of trucks waiting in queue and the average time of each truck to be attended. Video system also is considered to ensure that truck attendance occurs following the appointments and guarantee the security in the port area.

Moreover, RFID readers identify the cargo transported, while OCR is adopted to check documents and automatize the process. The connection technologies transfer data in real-time to the system, which will be processed with Big Data technology, and when all procedure is finalised, the automatic gate allow trucks to access the port. The use of smart technology can reduce the processing time of trucks in entrance operation. Figure 7 presents the model detailing the relationship between the different port logistic system members.

Figure 7 Conceptual model for a flexible TAS operation.



4.4.2 RESCHEDULING POLICIES

To design a future generation of TAS to allow the flexible rescheduling in response to unpredictable circumstances, we defined rescheduling policies to support our model. Besides, to operate dynamically, when a disruptive event is identified, the system will automatically propose rescheduling and inform the truck drivers about the scheduling update. We based the rules to propose reschedule in the data collected from port logistic system members and developed four main rescheduling rules:

- Delay detected from real-time location – based on historical data from past events, the system can categorise the data and identify when a truck is late. Moreover, from this perception the system should be capable of detect if the delay is recoverable or non-recoverable, and so, propose the most suitable reschedule. Also, if the system detect that the truck is not moving without further information, an alert should be emitted to the driver smartphone to identify if some problem has occurred and when no signal is received back from the driver, a security alert should be triggered.
- Congestion identified on the transport route – as mentioned in the previous topic, our model integrates an API connected to GPS in the mobile device to collect real-time location. Thus, the adoption of API enables the identification of the transport route and consequently, the traffic monitoring to detect congestion and propose alternative routes, when possible. From the congestion identification, the system should operate in the same manner as in the first rescheduling rule, which means that congestions should be categorised into recoverable and non-recoverable delays and propose the most suitable reschedule.
- Unexpected events reported from the LSA – as the trucks should move first to the LSA, the truck procedures check performed should be able to identify the existence of irregularities, as cargo problems, and reschedule or even cancel appointments, if necessary. This strategic decision is based on the combination of past events and specific port rules, in which the analysis of past events aims to propose suitable reschedules and the port rules are used to guarantee that all procedures are correctly performed.
- Status of port gates – we consider that all port gates have the same automation level and operate with the same operational efficiency, so, the data for analysis of port gates status consists in sensors to detect the average time of truck entrance procedure, the average waiting time of each truck and the number of trucks in queue. From this information, our proposed approach can categorise and identify unexpected circumstances and propose solutions,

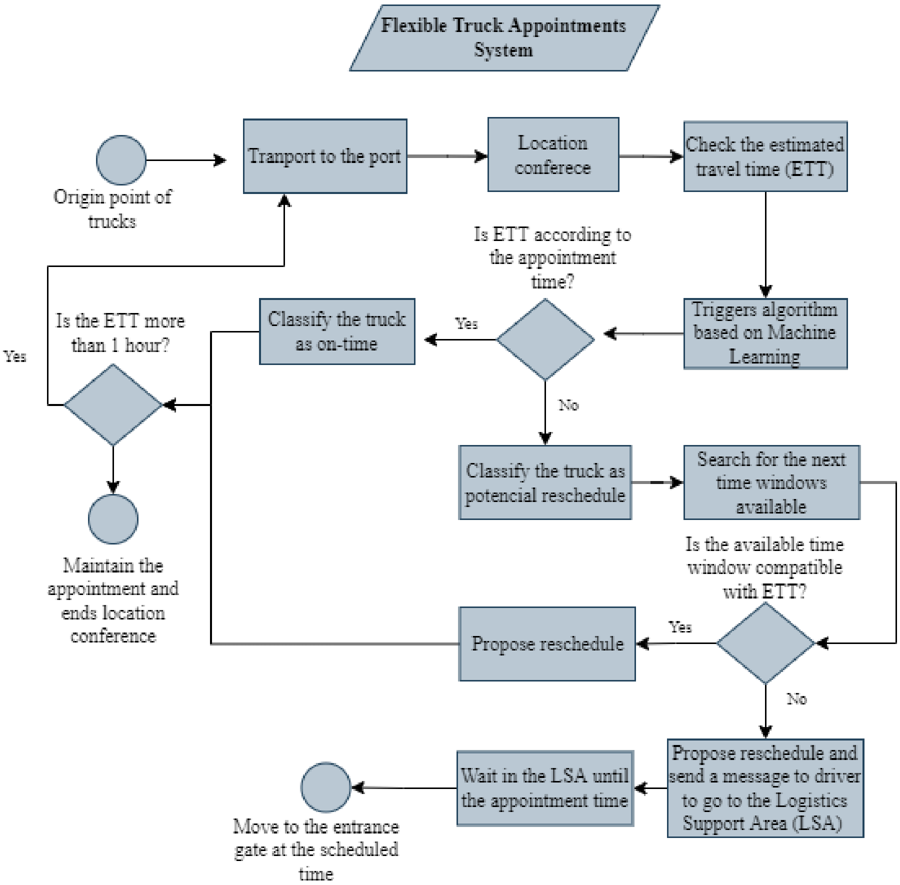
such as port gate maintenance and reschedule the appointments to the other port gates while the gate is not available.

4.4.3 DT APPROACH

The logic to support the real-time reschedule and allow the flexibility of the system will be based on the DT approach, in which the rescheduling policies presented in the previous topic will be applied to compare real-time data with historical data from past events and identify similar behaviours. From this identification, the system will categorise the real-time data and when an unexpected event occurs, the system dynamically suggests rescheduling the appointment. The conceptual model of our DT approach is presented in Figure 8.

Thus, the decision points presented in Figure 8 will be based on the comparison of real-time data with the historical data from past events, which allows the system to learn from past events and propose reschedule only when unexpected events are identified. Besides, this approach is capable of avoid decisions based on unclear circumstances, making the TAS more flexible and less susceptible to human errors.

Figure 8 Proposed conceptual model for the decision tree approach.



4.5 CONCLUSIONS

This paper designed a conceptual model of a flexible TAS for the operation of smart ports, based on ML approach. Therefore, this paper contributes to the theoretical literature by reviewing the concept of smart ports, identifying the main smart technologies applied in the context of port terminals, in addition to analysing the flexible schedule methods used in different areas and presenting a brief description of ML approaches identified in our review.

We identified that the DT is the most suitable ML approach to develop a flexible TAS, in which data acquired from smart technologies can be deployed to anticipate disruptions, classify the trucks in on-time, early or delay, and propose reschedule in the next available time windows when the disruption is detected. Also, we suggested a set of technologies to provide intelligence to port operation and to facilitate the decision-making regarding truck flow in the hinterland.

Moreover, as opportunities for future research, we aim to implement our conceptual model in a simulation scenario with real data from port terminals to identify the practical results of our approach and compare the performance of our model with a static TAS. As limitation, we mostly consider a Smart Port design for ports located near to urban areas, in which the truck flow can bring more negative impacts to the hinterland and the cities.

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5 INTEGRATION OF MACHINE LEARNING AND SIMULATION FOR DYNAMIC RESCHEDULING IN TRUCK APPOINTMENT SYSTEMS

Este artigo foi submetido na revista Simulation Modelling Practice and Theory.

Abstract

Traditionally, port terminals implement Truck Appointment System to control expected arrivals of trucks in port terminals. However, the occurrence of disruptions during transport causes unexpected circumstances, generating congestion and unbalanced arrivals at port hinterland. The use of smart technologies, in the context of Industry 4.0, is capable of collecting real-time geolocation and improve the visibility in the port logistics system, offering the opportunity to design a flexible TAS allowing dynamic rescheduling of truck appointments. In this sense, a new method combining a Machine Learning algorithm with discrete event simulation to predict truck conditions during the transport, and dynamically reschedule appointments of trucks classified as early and late trucks using real-time data acquired by smart technologies is proposed in this paper. The approach was evaluated in a Brazilian port terminal, and we use the average and the maximum waiting time of trucks in queue at the entrance gate, the average and the maximum number of trucks in queue at the entrance gate, and the percentage of trucks attended off-schedule as Key Performance Indicators. The Machine Learning accuracy was identified as 95.37% and the flexible method achieved a 90.4% improvement in the waiting time of trucks at port hinterland and a reduction of queue sizes compared to the current scenario, by the synchronization of arrivals in balanced time windows. Furthermore, this research contributes to increase the visibility in port logistics systems and reduce the vulnerability of port terminals.

Keywords: Machine Learning. Reschedule. Truck Appointment System. Port terminals. Port hinterland.

5.1 INTRODUCTION

The increase in commercial relations between countries from different continents in the globalized context has introduced the role of supply chain coordinator to port terminals [1]. According to the United Nations Conference on Trade and Development (UNCTAD) [2], approximately 80% of the global volume of goods uses maritime transport in the supply chain. In addition to showing the vital importance of port terminals in global logistics systems, this information presented by UNCTAD [2] places ports as the main actor in the global logistics system, with the responsibility to monitor, manage and coordinate the cargo flow. However, the high volume of cargo handled in port terminals also contributes to the emergence of several challenges for decision-making at ports, in order to maintain the operational quality of services [3, 4].

While the topics of port capacity and expansion [5], resources optimization [6], and the costs associated with congestion in the port area [7] are covered with consolidated results from researches, Yau et al. [8] points out that one of the main challenges for port authorities is to efficiently monitor and control the truck flow at port hinterland, avoiding queues and congestion. In order to deal with this challenge, traditional port terminals are undergoing a technological modernization, based on Industry 4.0 concepts, aiming to become Smart Ports [9,10]. However, even with the adoption of smart technologies, port terminals still must deal with operational problems related to demand, and so, the port authorities must consider the truck schedule and real-time monitoring of trucks during the transport time [11].

Azab et al. [12] highlight the importance of controlling and efficiently managing the truck flow at the port area, since more trucks are expected to deliver inbound containers from customers and receive outbound containers. Besides, the authors [12] comment that the high demand in port terminals creates a problem of synchronization of truck flow, in which many trucks arrive during the same time windows, generating high levels of congestion in port areas. Initiatives to manage the congestion at port terminals are being addressed with discrete-event simulation (DES) and technologies adoption [13], balancing the transport flow [14], and user equilibrium by road strategies [15].

In this context, Truck Appointment System (TAS) is used as an approach to reduce congestion by allocating truck appointments in specific time windows [16]. Moreover, the TAS can be combined with smart technologies to allow flexibility and avoid disruptive events, from the monitoring of truck flow [17,18]. The use of an adaptive TAS is an efficient solution to deal with unexpected circumstances in the supply chain, in which the use of flexible systems is being demanded by managers to simplify logistics operations [19,20].

Although the topic of flexible schedule is being more studied in the literature in the last decade, Da Silva et al. [17] identified that there is still a research gap in the port sector to design a flexible TAS and propose the use of Machine Learning (ML) approach to construct this method. ML is an approach to classify and predict behaviors based on historical data [21]. Examples of application of ML methods can be the prediction of the estimated time of arrival (ETA) in port terminals [22], the planning of resources [23], and optimise appointments [24]. To be integrated into a TAS, an algorithm based on ML approach should collect and monitor the real-time location of trucks in checkpoints during the transport to the port hinterland, identify the estimated travel time (ETT) to the port, and trigger the ML to classify the truck according to the appointment time.

Based on the challenging scenario described above for port terminals to control the truck flow at port hinterland, the main objective of this paper is to propose and evaluate a method to solve the rescheduling of appointments in TAS based on ML prediction for truck condition in real-time from the use of smart technologies to synchronize the port logistics system. To achieve this goal, a simulation model is developed to compare the results of the proposed method with a static scenario from data based on a use case of a Brazilian port terminal. Furthermore, to evaluate the performance of the method, we adopted the number of rescheduling requested in the system or the number of trucks attended off the schedule as a strategic Key Performance Indicator (KPI), and queue size and waiting time at port gate, as operational KPIs.

The remainder of this paper is organized as follows. The second section presents the related work and the contribution of our flexible TAS. The third section describes the studied problem, and the fourth section relates the simulation methodology. Section 5 explains the use case studied step by step, introducing the considerations of each scenario and the results obtained. Section 6 closes the paper with a conclusion and an outlook.

5.2 RELATED WORK AND CONTRIBUTION

Truck Appointment System (TAS) is a service approach used by port terminals to reduce the waiting time of trucks in queue for attendance at port gates, and thus avoid congestion in the port hinterland, through early receipt of information, which allow for more efficient planning by port authorities [16]. The first adoption of TAS in port terminals is known in the early 2000s in the US, in the port of Los Angeles, in order to better manage the flow of trucks, by balancing arrivals in time windows distributed throughout the day [25]. Since then, several port terminals around the world have adopted the use of TAS to coordinate truck flow, and studies to analyze and propose methods for optimizing schedules have been disseminated in the scientific field [26].

However, the functioning of TAS resulted in conflicts between port terminals and trucking companies, mainly due to unsuitable appointments assigned to truck companies and the charge of fines for unpunctual arrivals or strategic decisions regarding penalties for no-shows and late or early arrivals experienced in some terminals [12]. Azab et al. [12] also report that some terminals adopt strategies of forcing trucks arriving outside their scheduled time to wait at special waiting areas, such as logistics support area (LSA), to avoid congestion at port gates.

Over the years, different ways of implementing TAS started to be developed, and nowadays, the operation of a TAS can be classified into Static Truck Appointment System (STAS) and Dynamic Truck Appointment System (DTAS). On one hand, STAS is controlled by port authorities, defining the exact quota of every time window and adaptations and flexibility are not allowed in the system [27]. As the strategies adopted in STAS are rigid, no-shows and late or early arrival can easily become a problem at port gates. One example of STAS is presented in Wasesa et al. [28] that proposes an overbooking reservation mechanism to minimize the impact of no-shows by setting an overbooking ratio accordingly to historical data from the terminal. Another challenge for STAS is efficiently dealing with peak time and avoiding congestion, and the study of Xu et al. [29] presents a Mixed Integer Nonlinear Programming (MINLP) to impose constraints related to costs based on the queue size.

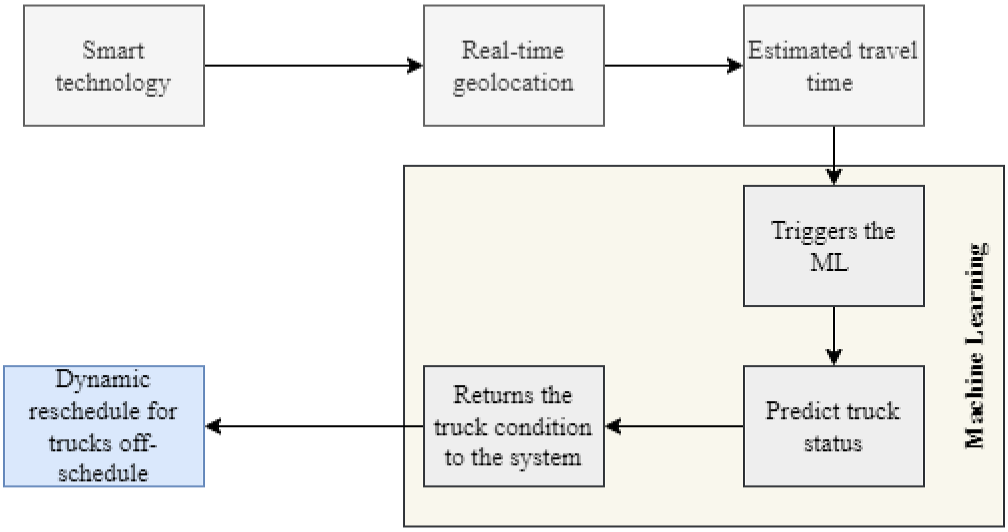
On the other hand, DTAS is more flexible and operates by allocating trucks in time windows according to queue length [27]. In addition to providing more efficiency for port terminals, a flexible scheduling system enables benefits to reduce penalties for transport companies, as the charging of fees for early or late arrivals, which is not usually the case in systems that allow rescheduling [25]. Aiming to propose flexible methods, the study by Li et al. [30] seeks to predict the occurrence of disruptive events in port terminals and provide data for decision-making of alternatives to increase the response capacity of these events from the synchronization of internal and external operations. Santos and Pereira [31] attempt to design a flexible model of operation integrated into TAS by creating a decision point to allow the access of trucks to primary port areas based on the current waiting time at the gate operations in the terminal.

In fact, support areas integrated into TAS are being considered as a complementary solution to develop flexibility in port operation and avoid congestion at port hinterland. Wibowo and Fransoo [32] integrate a drop-swap adjacent to the port terminal to receive empty containers and split the truck flow to minimize the existence of congestion. Frazzon et al. [11] consider a LSA functioning as a pre-gate operation located at the port hinterland, in which cargo and trucks are registered in the system and wait for authorization to access the port gate. So, the main idea is to reduce the truck flow using support areas to coordinate and directly communicate with the TAS.

Moreover, an integrated solution for TAS is proposed by Im et al. [33], in which the booking system is constructed based on cooperation between the truck companies and the port terminals. The method is developed from a mathematical model and the cooperation is obtained through the assignment of tasks to trucks accordingly to yard blocks and time windows [33]. However, we could not find any application of TAS collecting data from smart technologies to identify patterns of disruptive events and propose rescheduling to minimize the impact of these events in the port hinterland, and so, we characterize this topic as a research opportunity.

Therefore, the main contribution of this paper is proposing a new method that combines a Machine Learning algorithm with discrete event simulation to dynamically reschedule appointments of early and late trucks using real-time data acquired by smart technologies. From the solutions reviewed in the literature, we considered a LSA to synchronize the truck flow when the occupancy limit in the port area is reached. In this sense, the proposed solution in this paper consists of the use of smart technologies to synchronize the port logistics system flow and minimize the impact of late or early arrivals at port hinterland, in order to reduce congestion and develop a flexible TAS. Figure 1 presents the integration of smart technology, ML, and the dynamic reschedule of TAS in the model considered in our approach.

Figure 1 Conceptual integration of technology, ML, and reschedule



5.3 PROBLEM DESCRIPTION

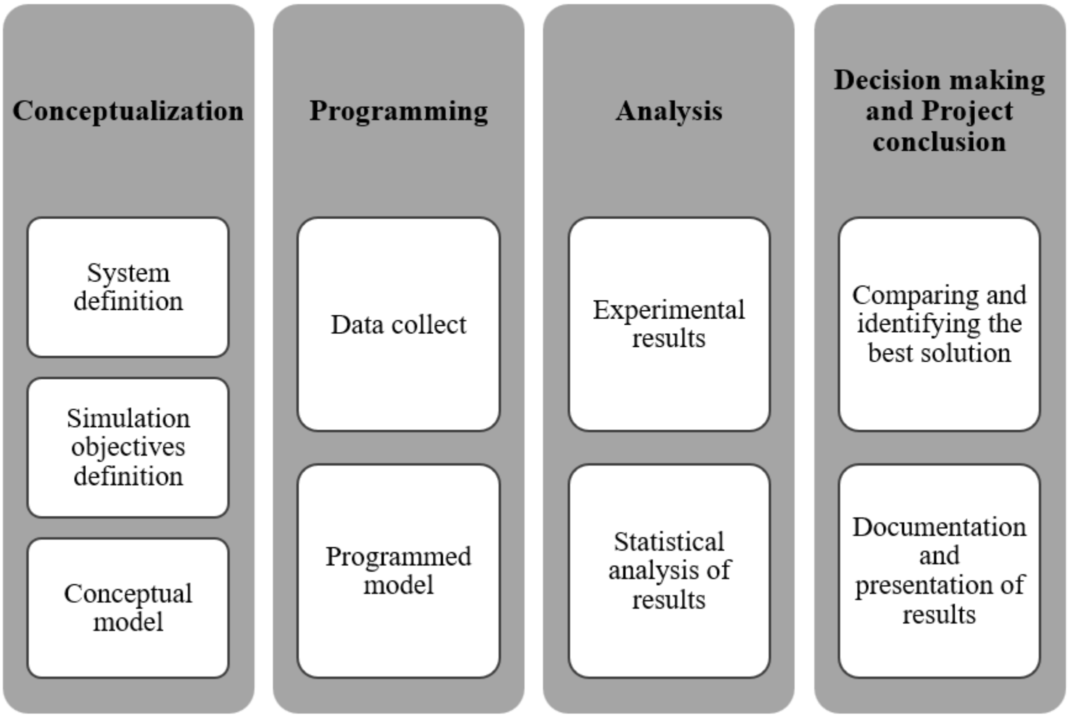
Considering a TAS system, the arrival of trucks can occur in four different ways. The first is on-schedule, when the truck arrives at the appointed time window, considered the ideal model of arrival since the port is expecting the truck. The second is an early arrival, which means that the truck arrives at the port hinterland before the appointment. In this case, the port terminals have the option of attending the truck before the appointed time windows or the truck should wait in port hinterland until the scheduled time, but both options can impact the truck flow at port hinterland, causing congestion and hindering the circulation of scheduled trucks. Also, the truck can arrive after the appointed time windows, forcing the port terminal to reschedule the attendance in another time window, and generating congestion, a long waiting queue, and an increase in emissions of pollutant, since the truck will wait for a new scheduled time at the port hinterland. Moreover, the port terminal must deal with non-appointed arrivals, a similar case to the late arrivals, in which the port is forced to find a time window for the truck while the truck is waiting in the port area and impacting the road flow.

Furthermore, not sharing real-time information between port logistics system actors can cause several problems, not only for port terminals but also for trucks, importers, and shipping companies. One of the main problems is that the entire logistics system is more vulnerable to disruptions since a problem in one member of the logistics system can affect the logistics flow in the entire supply chain. In this sense, synchronizing the real-time information from logistics members enables more visibility of the system and offers more resilience for the logistics system to adapt in the face of disruptions.

5.4 SIMULATION METHODOLOGY

To achieve the objectives presented in Section 1, we adapted the simulation methodology proposed by Chwif et al. [34], which is presented in Figure 2. The method is composed of four main steps: conceptualization, programming, analysis, and decision making, and project conclusion. In the conceptualization stage, the main goal is to define the concepts of the studied system and the simulation objectives, and then, design the conceptual model. The second stage is composed of data collection, which includes data analysis and processing, and the translation of the conceptual model into a computational model. The analysis stage starts with the experimental results and evolves to the statistical analysis of the final results. Finally, in the decision-making and project conclusion stage, the possible solutions are compared to identify the best approach, and the documentation and presentation of results are performed to conclude the project.

Figure 2 Simulation Methodology

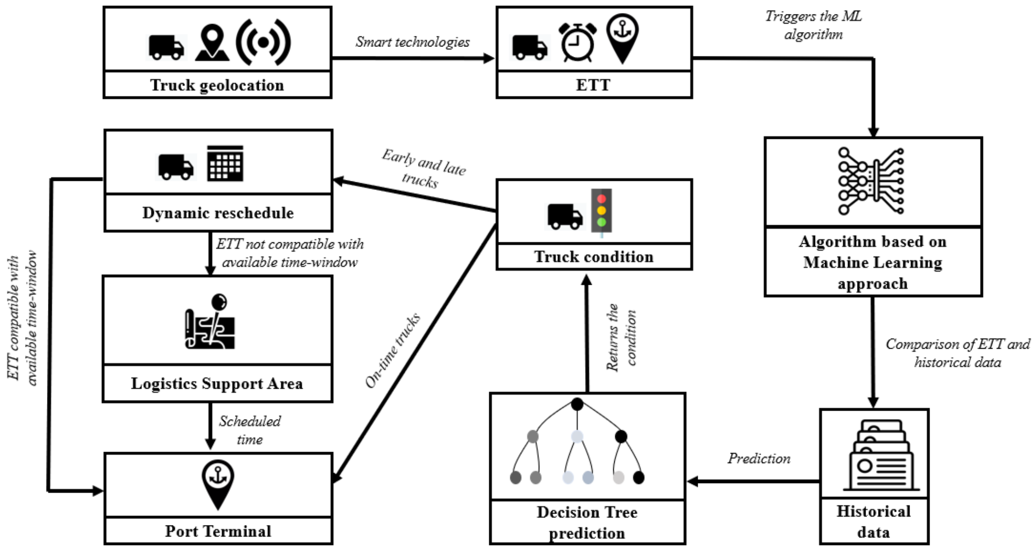


Source: Adapted from Chwif et al. [34]

To start the conceptualization, we defined the system studied in our case in Section 2 and described the problem in Section 3. The simulation objective is to analyze the impact of the use of ML to predict truck status in real-time and anticipate disruptions in the port logistics system, enabling the system to propose reschedule and synchronize the truck flow at port hinterland. This model is structured in the study of three scenarios: (1) Scenario 1 – non-flexible, not allowing rescheduling and without the use of smart technologies in the system; (2) Scenario 2 – non-flexible, not allowing rescheduling, but using a LSA to coordinate the truck flow and smart technologies to automatize the entrance process at port gates; (3) Scenario 3 – flexible, allowing rescheduling from the ML prediction, using a LSA to attend trucks arriving off-schedule and smart technologies to share real-time information, and automatize the entrance process at port gates. Moreover, we selected five KPIs to compare the results of the scenarios: average number of trucks in queue in the entrance gate, the maximum number of trucks in queue in the entrance gate, the average waiting time of trucks in queue in the entrance gate, the maximum waiting time of trucks in queue in the entrance gate, and percentage of trucks attended off-schedule.

As presented in Figure 1, the conceptual model considers the use of smart technologies, in the context of Industry 4.0, as Global Positioning System (GPS) installed in the smartphone of truck drivers and Radio Frequency Identification (RFID) to share the real-time geolocation of trucks, and then, calculate the estimated travel time (ETT) to the port terminal. From the ETT, the ML algorithm is triggered and based on historical data from the port terminal, a Decision Tree (DT) approach predicts the condition of trucks between on-schedule, early, or late. Then, the ML algorithm returns the truck condition to the system, and reschedules are proposed for the trucks classified as early or late, based on the ETT and the time windows available. However, if the ETT of the truck is not compatible with the available time window, the truck is directed first to the LSA, which works as a pre-gate near to the port hinterland, where the truck should wait until the scheduled time to access the port gate. Figure 3 presents a visual representation of the conceptual model. The programming, the analysis, and the decision-making stages are presented in Section 5.

Figure 3 Conceptual model for system integration



5.5 USE CASE

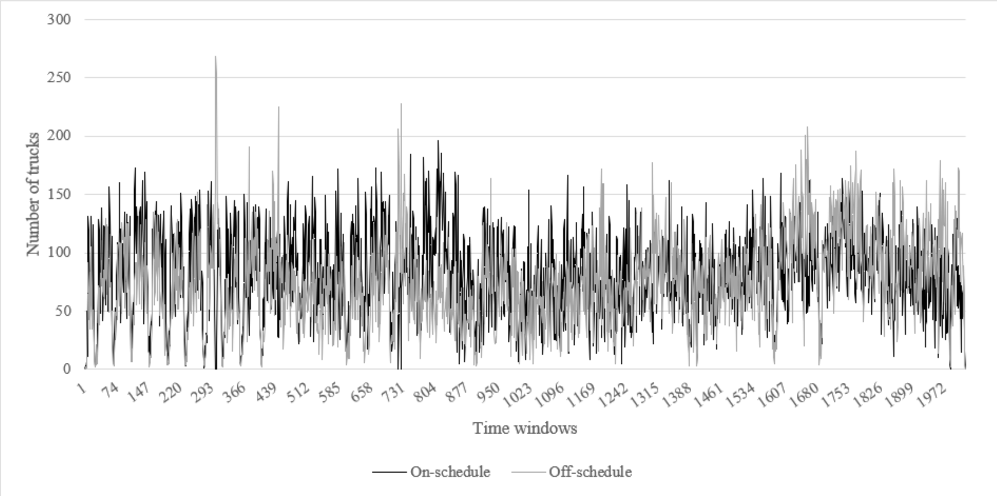
To test the model and evaluate the results of the proposed approach, we collected data from a Brazilian port terminal, specialized in container handling. We collected data from 20 months of operation at port gates and simulated one entire year of operation, which consists of around 316,000 truck attendances. Regarding the resources, we considered the operation with entrance gates, exit gates, and pre-gates in LSA. Also, as technologies we are considering GPS, RFID, and connection technologies to collect the real-time geolocation, OCR, smart sensors, and automatic gates to automate the entrance procedure, and video system monitoring to control the security and the truck coordination. As mentioned in Section 3, there are four different ways of truck arrivals, and we present in Table 1 the monthly percentage of arrivals for each category during the time horizon analyzed.

Table 1 Monthly distribution of truck arrivals in categories

Time	On-schedule	Early	Late	Non-appointed
Month 1	56.99%	21.33%	6.48%	15.20%
Month 2	53.67%	20.65%	6.09%	19.60%
Month 3	54.43%	21.82%	5.94%	17.82%
Month 4	59.31%	22.49%	4.07%	14.13%
Month 5	57.29%	22.00%	4.99%	15.71%
Month 6	56.96%	18.54%	12,71%	11.79%
Month 7	54.85%	18.10%	14.61%	12.43%
Month 8	49.75%	17.06%	15.86%	17.33%
Month 9	52.05%	18.79%	14.45%	14.71%
Month 10	47.94%	18.61%	15.27%	18.18%
Month 11	47.08%	17.17%	16.04%	19.71%
Month 12	43.94%	16.97%	18.80%	20.29%
Total	**52.41%**	**19.38%**	**11.53%**	**16.68%**

From Table 1, we can see the existence of a vulnerability in the scenario analyzed, in which the port terminal is dealing with a significant percentage of disruptive events during the entire time horizon. Even in the best monthly operation, the port registered 59.31% of trucks arriving on-scheduled, which means that 40.69% of the attendance occurred off-scheduled. Besides, in the worst monthly operation, only 43.94% of trucks arrived on schedule, and 56.06% arrived in unexpected circumstances at port hinterland. The yearly average is 52.41% of trucks arriving on schedule, which means that almost 50% of trucks arrive off-schedule, causing a disruption to the port logistics system and impacting the road flow at port hinterland. Furthermore, the TAS works in time windows of 14,400 seconds, which is the time that each appointment have to arrive on schedule at the port terminal. During one year of attendance, the TAS has around 2,000 time windows and the distribution of trucks arriving in each time window is presented in Figure 4.

Figure 4 Distribution of trucks in time windows



From the analysis of Figure 4, we can see that the port terminal faces peak time windows during the day, with more than 500 truck arrivals, and time windows with idleness, with less than 100 arrivals. Besides, the number of trucks arriving on-schedule and off-schedule is similar, with almost 50% for each, confirming the results of Table 1. Moreover, we performed data analysis and processing to ensure that no erroneous data were collected and that there are no outliers in the sample. So, to visualize the existence of outliers we plotted a graph representing the time between arrival of trucks at the time horizon of the scenario analysed, as can be seen in Figure 5. We also, conduct some analysis of the data, identifying the mean, median and the quartiles, as presented in Table 2.

Figure 5 Time between arrival of trucks

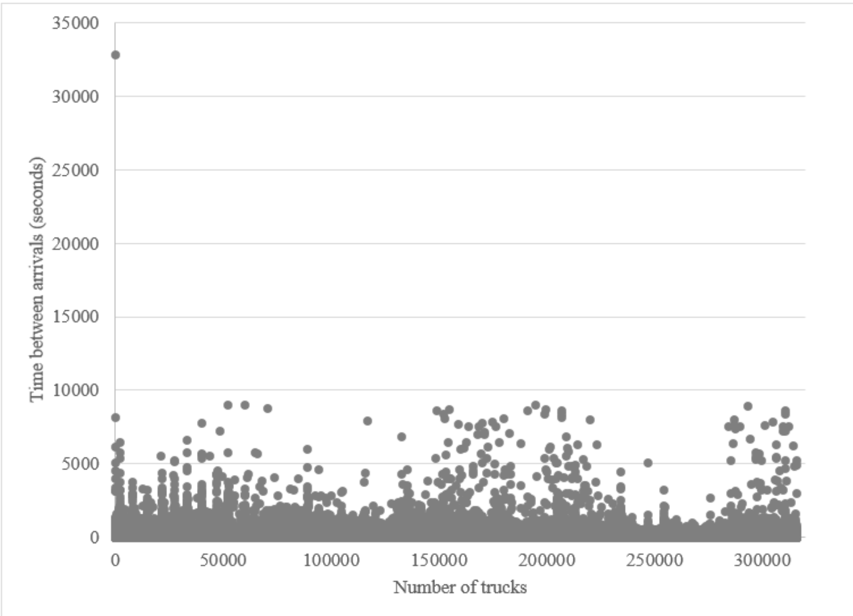


Table 2 Sample statistical information

Indicator	Sample - Time between the arrival of trucks
Minimum	0
Quartile 1 (Q1)	0
Quartile 2 (Q2)	60
Quartile 3 (Q3)	120
Maximum	32,820
Interquartile range (A)	120
Mean	92
Sample size	316,075

From the conference of data in the sample, we can observe the existence of a possible outlier in one of the first trucks arriving in the system, which has the time between arrival of 32,820 seconds or around 9 hours. We deeply analysed and identified that this data is regarding the first sample in the system, which means that the first truck arrived at the port terminal in the analyzed year occurred at 9 am, but there is no evidence that this data is a sample error, so we decided to consider the data in the simulation. Also, we can see by the Q1 analysis that more than 25% of trucks arrive at the port terminal with 0 seconds of difference from the last arrival, showing that there is a tendency for trucks to move in batches, especially when the trucks have the same origin point or are from the same company. So, considering that the only possible outlier identified in the sample was validated, we decided to consider the entire sample in our simulation.

5.5.1 EXPERIMENT DESCRIPTION

The simulation scenarios were implemented using Simmer: Discrete-Event Simulation package for R language [35]. The experiment was executed in a stochastic environment, which includes variations in arrivals, appointments, time windows and resources based on the historical data provides by the port terminal. Also, we used the Recursive Partitioning and Regression Trees (RPart) package for R language [36] to design the algorithm based on Machine Learning approach to classifying the truck condition.

We divided our model in three scenarios, as presented in Section 4. To define the number of replications, a pre-sampling was performed considering n = 30, which obtained mean = 491.66 seconds and relative standard deviation = 50.97 for the average waiting time.

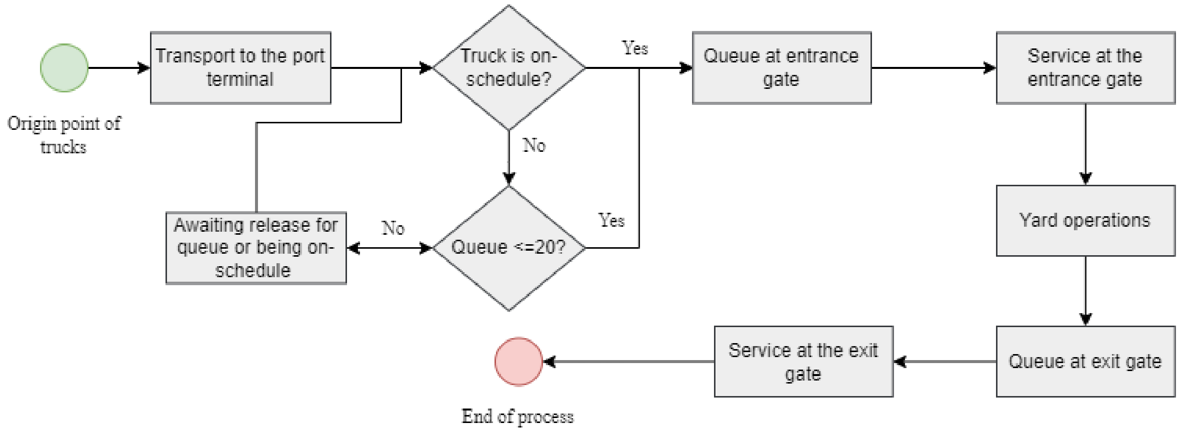
Assuming α = 0.05, the total number of replications was calculated as n = 17 for a percentage error = 0.05. From this, we decided to simulate each scenario 20 times, in which one year of port terminal operation was simulated in each replication. The computer used to perform the experiments has the processor Intel i7-10510U CPU @ 1.80 GHz 2.30 GHz.

5.5.1.1 SCENARIO 1

As explained in Section 4, scenario 1 is non-flexible and does not consider rescheduling of appointments, mainly due to the fact that this scenario does not include the use of smart technologies to collect geolocation and share information between port logistics system members. So, in this case, we are simulating the current scenario of the analyzed port logistics system in which there are only two moments of contact between truck companies and the port terminal. The first moment is when the appointment is scheduled on TAS with truck information, and the second contact is only when the truck arrives at the port terminal. So, considering the origin point of trucks, we inputted the transport time to the port terminal with a standard deviation consideration, and only when the truck arrives at the port terminal is verified if the arrival time matches with the time-window schedule.

The model considers that if the truck is on-schedule, their entrance in queue is allowed. Otherwise, if the truck is early, late, or is a case of a truck without scheduled time, the truck will wait at port hinterland for a signal to enter in the queue. The model only authorizes a waiting truck to enter in the queue when the total number of trucks in queue is less or equal to 20, considering the definition that the queue size should be compatible with the available area [37-38], or if the truck arrived early and after a while, the truck is on schedule. Every time a truck completes the process at the entrance gate, a check signal is sent to the off-schedule trucks to verify the condition and the number of trucks in the queue. Although our focus is on the entrance gate to verify the impact of flexibility in TAS in port hinterland flow, we are simulating the yard operation as a delay and the operation at the exit gate only to validate the results of our scenario. The flowchart showing the activities considered in the simulation of scenario 1 is demonstrated in Figure 6.

Figure 6 Scenario 1 flowchart

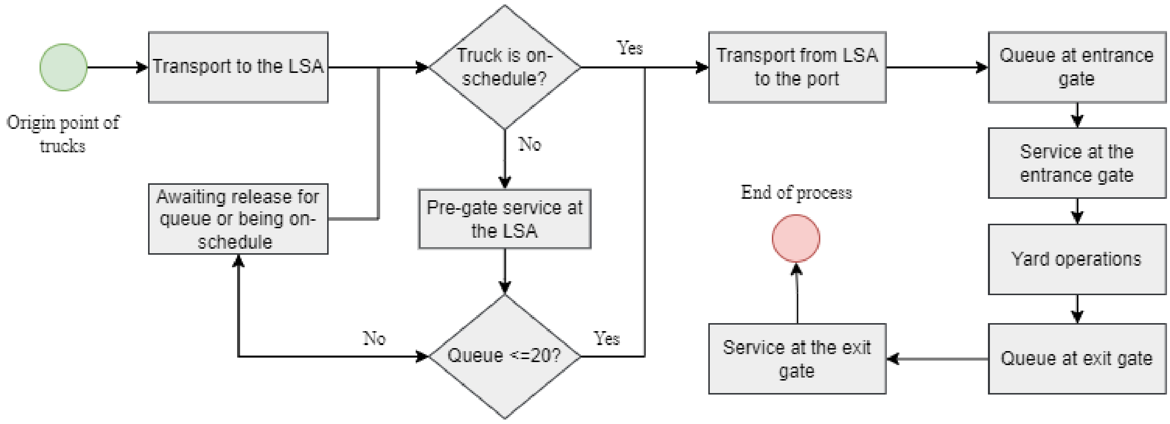


5.5.1.2 SCENARIO 2

The second scenario is intermediate between the non-flexible scenario 1 and the flexible scenario 3. In this scenario, the model still does not predict the truck status in real-time during the transport, but a LSA is included to support the coordination of truck flow and smart sensors and automation technologies are considered to optimize the service at the entrance gate with automated gates. So, with the insertion of a LSA, we indicate that the trucks should move from the origin point to the LSA, located around 40 km from the port terminal. In the LSA, the trucks check if the arrival time considering the estimated travel time from LSA to the port is compatible with the time window scheduled, and if the truck is considered on-schedule, the access is given to continue the transport to the port hinterland. On the other hand, if the truck is early, late, or do not have an appointment, there is a pre-gate service at the LSA to check the cargo documentation and update information for non-appointed trucks, and then, the trucks go through a process similar to scenario 1, checking if the total number of trucks in the queue at the entrance gate is less or equal to 20, or if the condition of the truck has changed to on-schedule.

The check definition is modified from scenario 1 and in this case, a signal is only sent to trucks to check the queue size and the condition when the queue size at the entrance gate is less than 20, enabled by the use of smart technologies at the port terminal to check the queue size in real-time. This signal is received for all trucks awaiting in LSA, and we defined the first-in-first-out (FIFO) rule to define which truck will be allowed to access the port hinterland. The sequence of the process is the same as scenario 1, so the truck will arrive at the entrance gate, wait in queue, perform the services at the entrance gate, pass for the yard operation and complete the process after passing for the exit gate. Figure 7 presents the visual flowchart for this scenario.

Figure 7 Scenario 2 flowchart



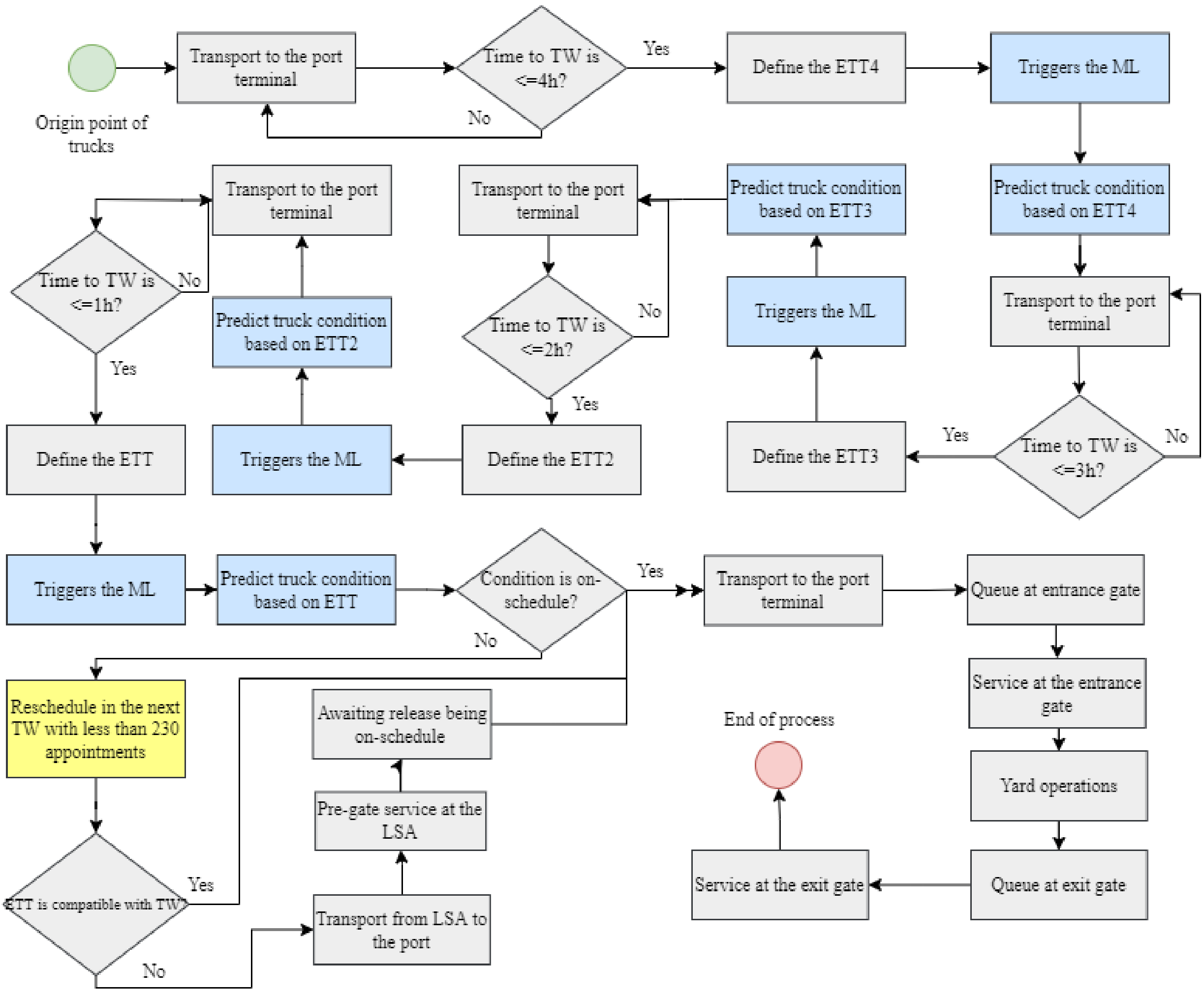
5.5.1.3 SCENARIO 3

The third scenario includes the ML prediction to propose reschedule of appointments and give flexibility to the system, and also considers the LSA to trucks with ETT not compatible with the time windows. So, in this scenario, the simulation starts in the origin point and the transport time of trucks to the port terminal have check moments of geolocation to estimate the ETT. In this sense, considering that each time windows (TW) have 14,400 seconds, the first check moment is considered 4 hours before the scheduled time window, in which the truck geolocation is collected with smart technology and the prediction of estimated travel time 4h before the appointment (ETT4) is determined. At this moment, the ETT4 triggers the ML, which predicts the truck status based on historical data, and returns the status for the system. Then, the truck continues the transport to the port terminal passing for checkpoints in each one hour, defining the estimated travel time 3h before the appointment (ETT3), the estimated travel time 2h before the appointment (ETT2) and the ETT. Trucks with less than 4 hours of transport sent the geolocation only in the time according to the transport time. Also, trucks without appointments are not considered in this part of the model.

When the truck is one hour away from the time window scheduled, the system checks the real-time geolocation for the last time, the ETT is determined, and the ML algorithm is triggered to perform the final prediction of truck condition. The condition is predicted between on-schedule, early, or late, and the algorithm returns the condition for the

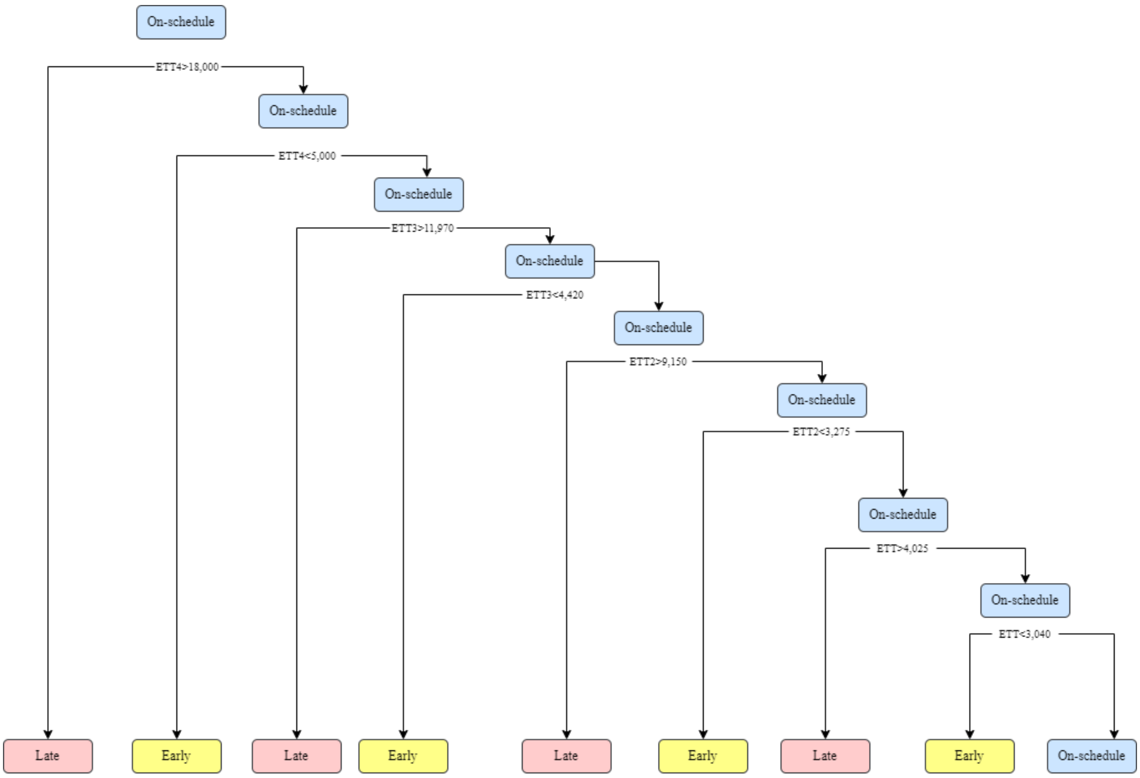
TAS. On one hand, if the condition is estimated as on-schedule, the truck continues the transport to the port terminal as scheduled, passing through the same process of scenario 1 and scenario 2, entering in queue at the entrance gate, and realizing the internal activities. On the other hand, if the condition is estimated as early or late, the system proposes a reschedule of the time window for the truck, identifying the next time window closer to the ETT with less than 230 appointments, which is the terminal capacity per time window. In sequence, we compare the new time window with the ETT, and if the arrival time is compatible with the time window, we allow the truck to move direct to the port terminal, but if the arrival time is not compatible with the time window, the truck should move first to the LSA, realize the pre-gate service, and wait there until the scheduled time. Besides, non-appointed trucks should always go before to the LSA and receive an appointment there, only being allowed to access the port hinterland in the scheduled time window. The reschedule methodology used in this paper is first detected, first served. Figure 8 presents the flowchart of scenario 3.

Figure 8 Scenario 3 flowchart



In order to simplify the model, we decided to perform the reschedule only one hour before the TW, considering the predictions realized before to increase the visibility in the logistics system and prepare the logistics members to be aware of any disruption. So, the prediction of ML is performed with the Decision Tree approach, which consists in the use of binary decisions to classify events. In our case, we used almost 250,000 appointment, real-time location and attendance data to train the model and achieved an accuracy of 95.37% in the predictions realized in our model. The logic behind the DT consists in identifying the intervals in which the ETT corresponds to on-schedule, early, or late trucks. Since the most complete prediction occurs one hour before the appointment when the system already has the ETT4, ETT3, ETT2, and ETT, the logic in this part is presented in Figure 9.

Figure 9 Decision Tree classification



5.5.1.4 RESULTS AND DISCUSSION

First of all, to validate the model we used the approach of Sargent [39], which consists in comparing the results of simulated scenario 1 with the real scenario, validating the results with historical data, and the results are presented in Table 3. We can see that the average waiting time in queue in the simulated scenario was 486.71 seconds, while the real scenario was 509.25, which represents a time difference of 22 seconds, mainly explicated due to the standard deviation we inputted in the transport time in our model. Also, regarding the maximum waiting time, our model identified 24,819.7 seconds, or 6.89 hours, while the real scenario is 25.775,2 seconds or 7.16 hours. The percentage of trucks attended off-schedule in the simulated scenario was 49.18%, which reveals a difference of 1.59% compared to the real scenario. This difference is explained due to the use of standard deviation in the transport time of the collected sample, which impacts mainly the trucks arriving at the end and the beginning of the scheduled time window. We could not compare the data regarding the average number of trucks in queue and the maximum number of trucks in queue with the real scenario, considering that the port terminal does not have this information. So, since we are taking into account an acceptable error of 5% in our model and the KPIs we are analyzing resulted in values under this value, we can consider that our model is validated with the reality and the difference between simulation and the real scenario is due to computational parameters.

Table 3 Validation of simulated scenario with real scenario

KPI	Simulated scenario 1	Real scenario	Difference
Average waiting time of trucks in queue in the entrance gate (s)	486.71	509.25	-4.42%
Maximum waiting time of trucks in queue in the entrance gate (s)	24,819.7	25,775.2	-3,71%
% of trucks attended off-schedule	49.18%	47.59%	1.59%

Considering that the model is validated, we have the objective of comparing the results of a non-flexible approach for TAS, an intermediate scenario, with a non-flexible, but considering smart technologies, and a flexible TAS based on the use of smart technologies to enable the prediction of the ML algorithm. To achieve this goal, we performed 12 months of simulation for each scenario. The results of the five KPIs we are analyzing are presented in detail in Table 4.

Table 4 KPI analysis

KPI	Scenario 1	Scenario 2	Scenario 3
Average waiting time of trucks in queue in the entrance gate (s)	486.71	112.83	46.70
Maximum waiting time of trucks in queue in the entrance gate (s)	24,819,7	1,431.1	1,305.4
Average number of trucks in queue in the entrance gate	5	3	1
Maximum number of trucks in queue in the entrance gate	120	33	30
% of trucks attended off-schedule	49.18%	41.05%	19.03%

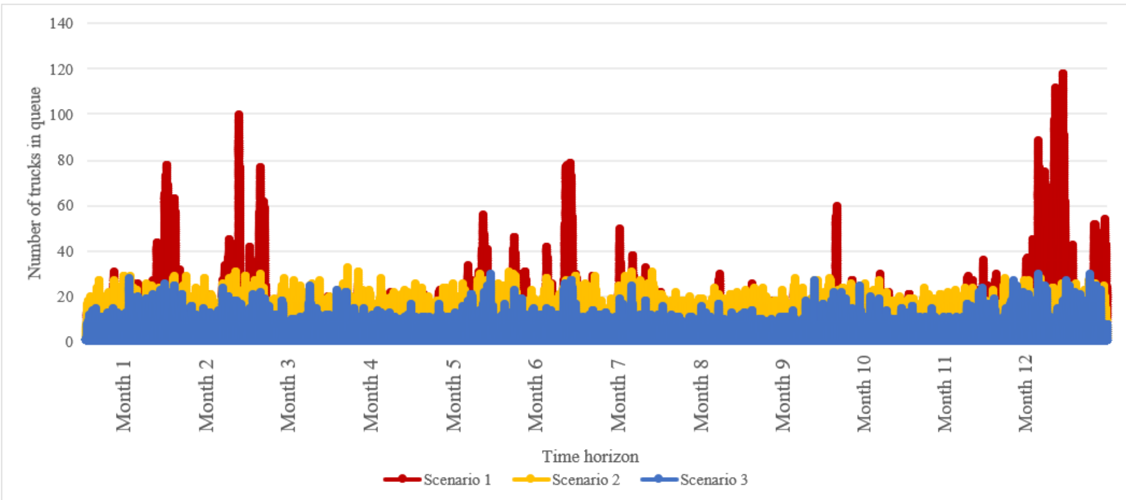
Scenario 1 achieved the worst results, showing that in peak hours the port terminal must deal with 120 trucks in queue, which generates a waiting time of almost 7 hours, representing congestion and problems at port hinterland. The average number of trucks in queue is around 5 trucks, which is a small number, but this value is mainly due to the fact that during night TW, there is a tendency of idleness at the port terminal, as shown in Figure 4, and then, the average number of trucks in queue shows a minimized number. Scenario 2 performed better than scenario 1, reducing the maximum number of trucks in queue by 72.5%, in a scenario in which the peak hours have results more acceptable and compatible to the reality of a terminal located in a city area and not impact significantly the road flow at port hinterland. However, this scenario is considering that 41.05% of the trucks attended in the port terminal must go first to a LSA, which represents around 130,000 trucks per year, and to allow this scenario to be implemented, the port terminal would have to implement a LSA with high capacity and area available, dispending a big operational cost.

Finally, the flexible approach proposed by this paper achieves a significant improvement compared to the other two scenarios without the need for a LSA with a capacity to attend 40% of the port flow. As mentioned in topic 5.1.3, the Decision Tree algorithm achieved an accuracy of 95.37% to classify the truck condition in real-time, and from this prediction, the model is capable to propose reschedule and coordinating the truck flow, synchronizing the port logistics system. In this scenario, the average waiting time of trucks in queue decreased 90.4% compared to scenario 1 and 58.6% compared to scenario 2, while the maximum waiting time of trucks in queue reduced by 94.7% compared to the current scenario. Besides, the average number of trucks in queue was identified as 1, while the maximum number of trucks in this scenario was 30, showing that the use of smart technologies is efficiently to coordinate the truck flow. Regarding the compatibility of the new time window scheduled for trucks and the estimated travel time, the percentage of trucks attended in LSA shows that the model is capable of adapting the appointments and creating a better synchronism for the logistics system, and only 19.03% of trucks required the LSA.

The improvement in the KPIs also indicates financial benefits for port terminal and trucks, since a fee regarding delay or no-show is no longer applicable in this scenario. The average number of trucks in queue less than 1 points out a possibility to consider more appointments in the terminal, as long as the arrivals are balanced and efficiently controlled, which can result in significative monetary gains for the port terminal.

We also analyzed the truck flow during the 12 months of simulation to verify the impact of the proposed approach in system balancing and the occurrence of peak hours, which can be seen in Figure 10. The result demonstrates that in scenario 1 the truck flow is unbalanced and peak hours occurred frequently during the simulation time, impacting the port hinterland with congestion and long waiting time, while scenario 2 achieved better performance, more balanced and without peak hours distant to the reality of the terminal. The flexible TAS can generate an even better performance than scenario 2, with more balance in truck arrivals and reducing the existence of queue.

Figure 10 Truck flow during the simulation time



Besides the quantitative improvement in performance, the results achieved in the dynamic scenario can also represent a better relationship between port terminal and the city citizens, since the truck flow impact is reduced. Although the considered capacity and the number of trucks attended in the port terminal is the same in the three scenarios, we can affirm that pollutant emission is also a possible contribution of our method, since the number of trucks in queue and the truck waiting time reductions impact the operational time of trucks, and, consequently, the pollutant emission is also reduced.

Therefore, the flexible approach proposed in this research was able to reduce the port logistics system vulnerability from the real-time monitoring of truck condition using smart technologies and a Decision Tree algorithm. The flexibility implemented by the allowance of reschedule for appointments and the use of a LSA balanced the truck flow and decreased the waiting time and the queue size at the port hinterland. The total computational time to simulate the scenarios was approximately 23 minutes for scenario 1, with each replication during about 1.15 minutes, 25 minutes for scenario 2 or 1.25 minutes for replication, and 310 minutes for scenario 3, representing approximately 15.5 minutes for each replication.

5.6 CONCLUSIONS AND OUTLOOK

The main contribution of this paper was to propose a new method that combines a Machine Learning algorithm with discrete event simulation to dynamically reschedule appointments of early and late trucks using real-time data acquired by smart technologies. We evaluated the rescheduling of appointments based on ML prediction for truck conditions during the transport time and the impact of enabling reschedule in the synchronization of port logistics system. To achieve the goal of this paper, we performed experiments of three scenarios, considering a non-flexible and without smart technologies scenario, representing the current scenario of the port system analyzed, an intermediate scenario non-flexible, but using smart technologies and a LSA, and a flexible scenario, acquiring data from smart technologies and proposing rescheduling of appointments based on ML prediction, and proved by the simulation of a use case that the flexible TAS proposed is capable of minimizing the congestion at port hinterland, reduce waiting time and create visibility in the supply chain, enabling the identification of unexpected circumstances, and then proposing rescheduling of appointments. To the best of our knowledge, there is no similar approach implemented in the literature, and similar studies are focused on evaluating the capacity and resource use at port terminals to minimize the queues.

This paper implemented an innovative approach in port logistics area, using Machine Learning to predict truck conditions in real-time based on historical data, and achieved

95.37% accuracy using almost 250,000 data to train the model, which is considered a good performance. A limitation of our study is that we only considered first detected, first served to reschedule the appointments, and different priority rules can be tested to compare the results, being an opportunity for future researches. Furthermore, we intend to expand our method in the future to integrate the TAS with a truck backhaul system, avoiding empty trips for trucks and reducing the pollution levels. Also, the human factors in the port logistics system are a good opportunity for analysis, testing the decision-making of humans from the use of smart technologies in port systems.

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6 SÍNTESE DO ESTUDO

Este capítulo apresenta a síntese do estudo em conformidade com os objetivos da dissertação. Na primeira seção do capítulo é abordada, de forma individual, a contribuição dos artigos que constituem a dissertação. Já a segunda seção apresenta a contribuição do estudo desenvolvido para o estado da arte na área de conhecimento em que esta dissertação está inserida, que pode ser visualizada na Figura 1, apontando para direcionamentos estratégicos e operacionais práticos para o funcionamento de sistemas logísticos portuários inteligentes.

6.1 RESUMOS DAS CONTRIBUIÇÕES DOS CAPÍTULOS

Os capítulos 4 e 5 que compõem essa dissertação são relativos à artigos científicos, formando a estrutura de compêndio de artigos para apresentação dos resultados deste estudo. Dessa forma, o Quadro 2 resume os principais resultados e contribuições de cada capítulo para a fundamentação da dissertação.

Quadro 2 - Resumo dos resultados e contribuições dos capítulos desta dissertação

		Objetivos	Resultados	Contribuições
Etapas 1 e 2	Capítulo 4	Projetar um modelo conceitual de *Truck Appointment System* flexível integrando dados de tecnologias inteligentes para identificar eventos disruptivos e reprogramar dinamicamente os atendimentos, evitando atrasos e controlando o fluxo de caminhões na hinterlândia portuária.	(1) O tema pesquisado é uma oportunidade de pesquisa inovadora; (2) O conceito de *Smart Ports* e as tecnologias que compõem um ambiente inteligente ainda não são consenso na literatura; (3) *Machine Learning* é o principal método utilizado para proporcionar flexibilidade em *schedule*; (4) A abordagem de *Decision Tree* pode ser caracterizada como a mais adequada para construção de um TAS flexível; (5) Desenvolvimento de um modelo conceitual para o funcionamento de um TAS flexível.	A análise performada permitiu uma visão geral do estado da arte sobre Portos Inteligentes e a identificação dos principais métodos para construção de um modelo de *schedule* flexível. Assim, foi possível propor um conceito para *Smart Ports*, apresentar tecnologias inteligentes para a melhoria do desempenho operacional da hinterlândia portuária e estruturar um modelo conceitual de TAS integrando tecnologias inteligentes e decisões baseadas no funcionamento da abordagem de *Machine Learning*.
Etapa 3	Capítulo 5	Desenvolver um modelo de simulação para avaliar o uso da abordagem de *Machine Learning* para permitir o reagendamento em um TAS, e comparar os resultados do método proposto com um cenário estático em um caso teste em um terminal portuário brasileiro.	(1) Tradução do modelo conceitual em um modelo computacional e simulação de três cenários analisando o impacto de tecnologias inteligentes e método flexível de agendamento nos indicadores de desempenho portuários. (2) O modelo flexível de TAS apresentou performance superior aos demais cenários para todos os KPIs analisados.	Os experimentos realizados possibilitaram a validação da eficiência do método flexível de TAS construído e demonstraram o impacto significativo do uso de tecnologias inteligentes e *Machine Learning* para aumentar a visibilidade e a coordenação de movimentos no sistema logístico portuário. Ademais, a abordagem inovativa usando *Decision Tree* atingiu um índice de acuracidade de 95, 37% em relação à classificação da condição dos caminhões durante o transporte.

Fonte: Elaborado pelo autor (2022).

O capítulo 4, referente ao primeiro artigo que compõe esta dissertação, apresentou o passo-a-passo da revisão sistemática de literatura conduzida, por meio do método PRISMA, na temática de Portos Inteligentes, e também para a identificação dos métodos para construção de *schedule* flexível em diferentes ambientes. Nesta etapa, foi verificado que os dois temas pesquisados são relativamente novos e estão recebendo maior atenção desde 2015, porém não foi identificado um estudo integrando as duas temáticas e, portanto, a utilização de conceitos e tecnologias inteligentes no ambiente portuário para construção de um sistema flexível de sincronização do sistema logístico foi identificada como uma oportunidade de pesquisa inovadora.

Ainda, em relação ao tema de Porto Inteligente, foi visualizado que os estudos existentes ainda estão voltados para a definição de conceitos, mas não há um consenso entre os autores pesquisados sobre o que torna um terminal portuário inteligente, assim como também não foram encontrados trabalhos práticos em terminais portuários para análise do uso de inteligência em indicadores operacionais rodoviários. Dessa forma, foi proposto um conceito para Portos Inteligentes a partir da visão dos autores analisados e um conjunto de tecnologias inteligentes foi apresentado para tornar o processo de monitoramento dos processos envolvidos no funcionamento de um TAS autônomo e dinâmico. Por outro lado, em relação ao tema de métodos flexíveis de *schedule*, foi identificado que um método pode ser adaptado para aplicação em contextos diferentes, ou seja, um método de *schedule* flexível para o agendamento de pacientes hospitalares pode ser adaptado para o agendamento de caminhões em um *gate* portuário, e, a partir disso, foi performada uma análise dos principais métodos utilizados, em que a abordagem de *Machine Learning* sobressaiu em relação aos demais métodos identificados, devido aos resultados obtidos oportunizarem maior confiabilidade para a tomada de decisão estratégica.

Especificamente em relação às abordagens de *Machine Learning*, a busca realizada possibilitou a análise particular de métodos de aprendizagem supervisionada, já que o estudo a ser realizado possui dados pré-organizados, selecionados e com objetivos claros, o que caracteriza a abordagem supervisionada. Entre os métodos existentes, identificou-se que *Decision Tree* possui maior conexão com o problema estudado, já que é caracterizado como um método eficiente para classificar eventos a partir de dados históricos, havendo comprovação prática de que a abordagem apresentou acuracidade de 97% para classificação de eventos.

Portanto, o modelo conceitual desenvolvido no capítulo 4 foi embasado em uma extensa revisão de literatura de 120 artigos publicados em *journals* de língua inglesa, em que foram integrados conceitos de Porto Inteligente, assim como as tecnologias inteligentes para a sincronização do sistema logístico, para a correta tomada de decisão do algoritmo baseado em *Machine Learning* quanto à classificação dos eventos ao longo do tempo. A partir do modelo apresentado, foi identificado que é possível propor reagendamentos dinâmicos em tempo real e construir um TAS flexível utilizando uma área de suporte logístico para apoiar a sincronização do fluxo rodoviário, possibilitando um pré-atendimento de caminhões fora da janela de agendamento neste local.

Já no capítulo 5, referente ao segundo artigo que compõe essa dissertação, foram apresentados os experimentos computacionais simulados para a análise dos resultados do modelo conceitual desenvolvido no capítulo 4. Em um primeiro momento é descrito o problema estudado, caracterizando a necessidade de aumentar a visibilidade ao longo do sistema logístico portuário para identificar a chegada de caminhões fora da janela agendada, e consequentemente, reduzir a vulnerabilidade dos membros do sistema logístico. Também é apresentada a metodologia adotada para a condução da simulação de eventos discretos, baseada em aplicações consolidadas.

Seguindo a metodologia adotada para a simulação de eventos discretos, são apresentadas as principais informações dos dados coletados e o processo de análise de *outliers* na amostra. Como não foram identificados *outliers* oriundos de má coleta de dados, passou-se para a etapa de validação do modelo computacional. A validação foi realizada a partir dos resultados do modelo referente ao cenário 1, já que esse modelo representa a realidade atual do terminal portuário usado para estudo, sem considerar a possibilidade de reagendamento e também sem considerar o uso de tecnologias inteligentes. Os resultados desse cenário foram usados para comparação com os valores coletados, e os dados foram considerados validados dentro do parâmetro de 5% de erro considerado no modelo.

Em relação aos cenários testados, o cenário 1 apresentou o maior tempo de espera dos caminhões na fila do *gate* de entrada, assim como o maior número de caminhões em fila e o maior percentual de caminhões atendidos fora do horário agendado. O cenário 2, que inclui principalmente o uso de uma área de suporte logístico para o pré-atendimento de caminhões fora da janela agendada, foi capaz de reduzir significativamente o tempo de espera e o número de caminhões em fila, porém requer a construção/uso de uma área com capacidade para atender mais de 40% da demanda portuária, que pode se tornar inviável economicamente e estruturalmente para o terminal portuário.

Por outro lado, o terceiro cenário simulado, que inclui a predição do algoritmo de *Machine Learning*, a partir da coleta de informação sobre a localização em tempo real dos caminhões a cada uma hora, e uma área de suporte logístico para atender apenas os caminhões com reagendamento não compatível com o tempo estimado de chegada no terminal, foi capaz de reduzir o tempo de espera e o número de caminhões na fila no *gate* de entrada, a partir da sincronização das chegadas e balanceamento das janelas de agendamento. Além de ter atingido um índice de acuracidade superior à 95% para a predição, o algoritmo de *Decision Tree* também foi eficiente em identificar no momento certo a necessidade de reagendamento, já que apenas 19% dos caminhões necessitaram passar pela área de suporte logístico devido à problema de compatibilidade entre o agendamento e o tempo estimado de chegada.

Dessa forma, o método construído demonstrou eficiência para sincronizar o sistema logístico portuário a partir do monitoramento de informações rodoviárias em tempo real. A união de tecnologias inteligentes com o uso de métodos flexíveis é uma oportunidade de alcançar resultados significativamente positivos em ambientes portuários e oferecer benefícios para os membros do sistema logístico.

6.2 CONTRIBUIÇÕES TEÓRICAS DA DISSERTAÇÃO E IMPLICAÇÕES GERENCIAIS

O advento da Indústria 4.0 originou uma necessidade de desenvolvimento de estudos para redefinição de processos existentes. No contexto portuário, o uso de sensores e tecnologias para fornecer inteligência às operações é um tema inovador e complexo, devido ao número de processos existentes e da quantidade de informações envolvidas na tomada de decisão. O estudo do tema é justificado pela relevância do setor portuário para a economia global, em que o tema oferece contribuições que transcendem a teoria e podem auxiliar na melhoria do desempenho de sistemas logísticos portuários, a partir da reprogramação dinâmica e flexível.

A ausência de estudos envolvendo o uso de tecnologias inteligentes para o desenvolvimento de um TAS flexível em terminais portuários e os estudos com aplicações práticas e testes do funcionamento de Portos Inteligentes foram as principais lacunas identificadas na revisão de literatura. Tendo em vista a criteriosa metodologia utilizada na revisão de literatura, com a aplicação do método PRISMA para dar credibilidade ao estudo, é possível considerar que a inexistência de trabalhos no contexto deste estudo comprova o ineditismo do tema pesquisado.

Ademais, a revisão sistemática de literatura foi crucial para a seleção de tecnologias para o funcionamento do sistema logístico portuário inteligente, assim como, a tomada de decisão referente ao método adotado para fornecer flexibilidade ao TAS. Aliás, a falta de estudos sobre *schedule* flexível no ambiente portuário estabeleceu a necessidade de expansão da revisão para diferentes contextos, embasada em estudos práticos anteriores que consolidaram a possibilidade de tradução de um mesmo método para ambientes distintos.

Assim, essa dissertação aborda contribuições teóricas para a discussão científica sobre o conceito de Porto Inteligente, assim como a integração de informações no sistema logístico portuário para a formação de *schedule* flexível. Além do debate acadêmico, o modelo desenvolvido pode ser utilizado como referência prática para implementação de sistemas inteligentes em terminais portuários, já que o estudo foi construído de forma genérica, visando atender à necessidade de diferentes terminais portuários.

Em relação aos resultados práticos obtidos, a análise realizada a partir da simulação dos três cenários implica na comprovação de que a integração de tecnologias inteligentes e métodos de gerenciamento flexíveis é capaz de melhorar o desempenho de indicadores operacionais e estratégicos, além de contribuir para o aumento da visibilidade ao longo do sistema logístico portuário em tempo real. Ademais, o estudo realizado oferece uma alternativa gerencial para os terminais portuários que precisam lidar com congestionamento na hinterlândia, especialmente os terminais localizados em centros urbanos e que não dispõem de área adicional para expansão física, porém precisam lidar com aumento contínuo de demanda, que acarreta longos tempos de espera e congestionamento na hinterlândia portuária.

7 CONSIDERAÇÕES FINAIS

Esta dissertação propôs um método de sincronização do sistema logístico portuário a partir do monitoramento rodoviário oriundo da coleta de informações em tempo real possibilitada por tecnologias inteligentes e integração dessas informações no *Truck Appointment System* para definir a necessidade de reagendamento dos caminhões. O modelo pode ser considerado inovador, já que não foi encontrada nenhuma evidência da existência de métodos similares no contexto portuário.

Ainda, este estudo foi dividido em quatro etapas para atingir o objetivo geral e os quatro objetivos específicos traçados. Na primeira etapa, denominada de análise e revisão da literatura, foi performada uma revisão sistemática das temáticas que suportam o desenvolvimento deste estudo, em que foi possível definir o conceito para portos inteligentes e apresentar tecnologias inteligentes com melhores resultados para redução de congestionamento na hinterlândia portuária, atingindo o objetivo específico (a), e também identificar métodos de agendamento de chegadas com flexibilidade em diferentes ambientes, desde que o método permitisse a adaptação para o contexto portuário, concluindo o objetivo específico (b).

Na segunda etapa do estudo, um modelo conceitual foi proposto combinando tecnologias inteligentes e métodos flexíveis de agendamento de chegadas, de forma a solucionar o objetivo específico (c). Ao final desta etapa, foi estruturado um artigo para publicação e disseminação dos resultados conceituais obtidos a partir da soma da análise e revisão da literatura realizada na etapa 1 e do desenvolvimento conceitual elaborado na etapa 2.

A terceira etapa do estudo, que consiste no desenvolvimento computacional e aplicação do método foi iniciada com a coleta de dados reais em um terminal portuário brasileiro para basear as informações do estudo. Ainda, o modelo conceitual foi traduzido em um modelo computacional, por meio da linguagem de programação em R, e foi feita a comparação, por meio de simulação de eventos discretos, da quantidade de veículos em fila no *gate* portuário em diferentes cenários, considerando atendimento estático e dinâmico, o que completou a execução do objetivo específico (d).

A partir dos resultados obtidos na simulação dos cenários analisados, um segundo artigo foi elaborado para a disseminação dos resultados desta dissertação, compondo a quarta etapa deste estudo. Assim, com os resultados alcançados nas quatro etapas é possível afirmar que o objetivo geral deste estudo, definido como desenvolver um sistema flexível de atendimento de caminhões e medir o impacto da sua utilização nos indicadores de desempenho logístico do sistema logístico portuário, baseado no compartilhamento de informações em tempo real, foi alcançado com a comparação do cenário atual do terminal portuário, considerado estático, e o cenário flexível, aplicando o método proposto.

Finalmente, os resultados obtidos na simulação permitem concluir que o método proposto é capaz de reduzir o tempo médio de espera dos caminhões em fila no *gate* de entrada, assim como o tempo máximo de espera dos caminhões, diminuir o número médio e máximo de caminhões em fila no *gate* de entrada, reduzindo o impacto do terminal na hinterlândia, e melhorar o índice de caminhões atendidos fora da janela agendada. Além dos indicadores quantitativos, o modelo ainda auxilia no aumento da visibilidade do sistema logístico portuário, possibilitando que o terminal acompanhe, em intervalos de tempo pré-definidos, a condição estimada dos caminhões com agendamento próximo no terminal e esteja menos vulnerável para a ocorrência de eventos disruptivos.

7.1 OPORTUNIDADES PARA ESTUDOS FUTUROS

Esta dissertação possui algumas limitações, as quais indicam oportunidades de pesquisa para estudos futuros. Primeiro, a consulta de diferentes bases de dados para realização de novas revisões de literatura, assim como a consulta do banco de dados de teses e dissertações da CAPES é uma oportunidade para estender a fundamentação teórica do estudo. Além disso, outros aspectos do modelo desenvolvido podem ser abordados, como o teste de acompanhamento da localização do caminhão pelo terminal portuário desde o ponto de origem do caminhão, invés de iniciar a coleta de informação apenas 4 horas antes do início da janela agendada, e também o teste da melhoria de desempenho do sistema com a proposição de reagendamento em cada uma das verificações de condição do caminhão. Essa hipótese de reagendamento a cada verificação de condição não foi abordada neste estudo devido ao tempo necessário de simulação para operacionalizar a hipótese, mas dependendo do grau de necessidade de detalhes do sistema, é uma função possível de ser colocada em prática.

Diferentes estudos de terminais portuários em diferentes contextos podem ser simulados, variando os parâmetros adotados neste estudo para analisar e comparar os resultados utilizando outros parâmetros, como diferentes regras de priorização para o reagendamento de atendimentos no terminal portuário. Ademais, aspectos como a emissão de poluentes e a interação porto-cidade podem ser exploradas com maior profundidade, a partir de adoção de indicadores de desempenho específicos para mensurar essas questões.

Ainda, este trabalho pode ser expandido para integração de outros problemas existentes no contexto portuário, como a contratação do frete de retorno. Em que o uso de um TAS flexível pode ser integrado à uma plataforma de contratação de frete de retorno para os caminhões e evitar a ocorrência de viagens vazias, assim como reduzir o número de caminhões circulando na área portuária. Ademais, a inclusão de fatores relacionados à manutenção e a escolha humana podem ser integrados ao modelo, para inserir a necessidade de manutenção dos caminhões e também dos equipamentos portuários, como os *gates* de entrada, e o impacto do fator humano na tomada de decisão dos sistemas inteligentes.

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