UNIVERSIDADE ESTADUAL DE CAMPINAS
Faculdade de Engenharia Mecânica

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Adoção dos conceitos da Indústria 4.0 nas empresas brasileiras de manufatura: análise dos principais desafios

CAMPINAS
2022

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Texto apresentado à Faculdade de Engenharia Mecânica da Universidade Estadual de Campinas para a obtenção do título de Mestre em Engenharia Mecânica, na área de Materiais e Processos de Fabricação.

Orientador: Prof. Dr. Rosley Anholon

ESTE DOCUMENTO CORRESPONDE À VERSÃO FINAL DA DISSERTAÇÃO DE MESTRADO APRESENTADA PELO ALUNO PEDRO GUILHERME SANCHES CONTIERI, SOB ORIENTAÇÃO DO PROF. DR. ROSLEY ANHOLON.

CAMPINAS
2022

Ficha catalográfica
Universidade Estadual de Campinas
Biblioteca da Área de Engenharia e Arquitetura
Rose Meire da Silva - CRB 8/5974

C767a
Contieri, Pedro Guilherme Sanches, 1995-
Adoção dos conceitos da Indústria 4.0 nas empresas brasileiras de manufatura: análise dos principais desafios / Pedro Guilherme Sanches Contieri. – Campinas, SP : [s.n.], 2022.

Orientador: Rosley Anholon.
Dissertação (mestrado) – Universidade Estadual de Campinas, Faculdade de Engenharia Mecânica.

1. Indústria 4.0. 2. Digitalização. 3. Manufatura. 4. Cadeias produtivas. I. Anholon, Rosley, 1979-. II. Universidade Estadual de Campinas. Faculdade de Engenharia Mecânica. III. Título.

Informações para Biblioteca Digital

Título em outro idioma: Industry 4.0 concepts and technologies in Brazilian manufacturing: analysis of main challenges
Palavras-chave em inglês:
Industry 4.0
Digitalization
Manufacturing
Production chains
Área de concentração: Materiais e Processos de Fabricação
Titulação: Mestre em Engenharia Mecânica
Banca examinadora:
Rosley Anholon [Orientador]
Paulo Sérgio de Arruda Ignácio
Robert Eduardo Cooper Ordoñez
Data de defesa: 26-01-2022
Programa de Pós-Graduação: Engenharia Mecânica

Identificação e informações acadêmicas do(a) aluno(a)
- ORCID do autor: https://orcid.org/0000-0003-3343-1627
- Currículo Lattes do autor: http://lattes.cnpq.br/8742943455075054

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DISSERTAÇÃO DE MESTRADO

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Campinas, 26 de janeiro de 2022

Resumo

A Indústria 4.0 é uma das ondas mais heterogêneas da industrialização global e o impacto das novas tecnologias no setor de manufatura é algo a ser explorado em diferentes contextos regionais. A presente dissertação apresenta uma abordagem exploratória do contexto brasileiro, visando expandir os conhecimentos acadêmicos sobre os graus de priorização de investimentos e desafios dos processos transitórios entre a terceira e a quarta revolução industrial. Neste contexto, foi desenvolvida uma *survey* direcionada aos tomadores de decisão do setor de manufatura, buscando captar a percepção de priorização e dificuldade de implementação das principais tecnologias habilitadoras da Indústria 4.0. Utilizando o algoritmo *Fuzzy-TOPSIS*, foram obtidos rankings nas duas métricas avaliadas, nos quais concluiu-se que digitalização no chão de fábrica e *IoT* figuram entre as tecnologias mais priorizadas para aplicação, enquanto Cibersegurança, robótica colaborativa e análise de *Big Data* figuram entre as de maior dificuldade de implementação. A seguir, foi desenvolvida uma pesquisa de conversão de uma célula de manufatura 3.0 para uma célula autônoma 4.0, em parceria com o SENAI, visando estudar em detalhes as dificuldades operacionais na implementação das tecnologias habilitadoras em um microcosmo industrial. À luz da literatura, foi possível avaliar cada uma delas e suas soluções, compreendendo suas interações sob uma perspectiva econômica das empresas do setor. Compreender o fenômeno da quarta revolução industrial em diferentes contextos é essencial para uma compreensão global da nova era da indústria, visando auxiliar pesquisadores e tomadores de decisão rumo ao futuro da indústria de manufatura, reduzindo os riscos e maximizando os investimentos.

Palavras Chave: Indústria 4.0, digitalização, manufatura, célula produtiva, países emergentes

Abstract

Industry 4.0 is one of the most heterogeneous waves of global industrialization and the impact of new technologies on the manufacturing sector is something to be explored in different regional contexts. This research presents an exploratory approach to the Brazilian context, aiming to expand academic knowledge about the levels of prioritization of investments and challenges on transitional processes between the third and fourth industrial revolution. In this context, a survey was conducted with decision makers of the manufacturing sector, aiming to capture the perception of prioritization and difficulty in implementing the main enabling technologies of Industry 4.0. Using a Fuzzy-TOPSIS algorithm, rankings were obtained in the two evaluated metrics, in which it was concluded that shop floor digitalization and IoT are among the most prioritized technologies for application, while Cybersecurity, collaborative robotics and Big Data analytics are among those of greater difficulty level of implementation. Next, a research on the conversion of a 3.0 manufacturing cell to a 4.0 autonomous cell was developed, in partnership with SENAI, aiming to study in detail the operational difficulties in the implementation of enabling technologies in an industrial microcosm. Considering the literature, it was possible to evaluate each of them and their solutions, understanding their interactions from an economic perspective of companies in the area. Understanding the phenomenon of the fourth industrial revolution in different contexts is essential for a global understanding of the new era of industry, aiming to help researchers and decision makers towards the future of the manufacturing industry, reducing risks and maximizing investments.

Keywords: *Industry 4.0, digitization, manufacturing, productive cell, emerging countries*

Sumário

1 INTRODUÇÃO

1.1 CONTEXTO DA PESQUISA

A discussão em torno do conceito da Indústria 4.0 vem evoluindo consideravelmente a cada ano (CULOT et al., 2020). Pesquisas em diferentes campos do saber têm buscado construir uma base de conhecimento a fim de melhor guiar as organizações no processo de transição para a revolução digital (NAKAYAMA; DE MESQUITA SPÍNOLA; SILVA, 2020). Tais pesquisas vão desde o mapeamento das principais tecnologias habilitadoras (WANG et al., 2016) até a compreensão dos impactos sociais e estruturais de uma sociedade intimamente conectada à cadeia de produção (JOST; SÜSSER, 2020). Para alguns pesquisadores (CULOT et al., 2020), a maior popularização das tecnologias habilitadoras e a difusão de casos de sucesso no setor industrial tendem a popularizar a ideia de que a quarta revolução industrial é um processo que já está em curso e não apenas algo para um futuro distante.

As tecnologias habilitadoras são caracterizadas como instrumentos base da nova revolução industrial, sendo elas os principais vetores do desenvolvimento tecnológico (KAGERMANN; WAHLSTER; HELBIG, 2013). Se caracterizam como os principais impulsionadores do conceito *Smart Factories*, que pode ser definido como um sistema produtivo totalmente monitorado, com computação decentralizada e capaz de tomar decisões sobre o próprio processo com base em dados coletados de toda a cadeia de suprimentos, de ponta a ponta (OSTERRIEDER; BUDDE; FRIEDLI, 2020).

Para Ghobakhloo, 2018 a manufatura se destaca como um dos primeiros setores a sentir as mudanças estruturais e a quebra de paradigma representada pela quarta revolução industrial (GHOBAKHLOO, 2018). Tais mudanças apresentam-se de formas distintas nas diferentes regiões do mundo, a depender das condições socioeconômicas, geográficas e políticas de cada país. Desta forma, o processo de expansão da Indústria 4.0 é caracterizado como pouco homogêneo (SCHROEDER et al., 2019; SONY; NAIK, 2020), apesar da alta velocidade esperada para sua disseminação. Compreender os fenômenos culturais de cada país torna-se essencial para melhor definir os rumos a serem trilhados por uma nação.

Estudos bibliométricos recentes (KIPPER et al., 2021) apontam a crescente onda de pesquisas coordenadas de conjuntura e dos elementos pontuais que caracterizam a quarta revolução industrial. Os estudos conjunturais visam explorar e compreender a relação entre os novos elementos da quarta revolução industrial e a sociedade, tanto em questões econômicas quanto nas transformações das relações sociais (FUKUDA, 2020). No campo econômico, o direcionamento de investimentos das principais empresas do mercado pode significar um direcionamento para o mercado como um todo, seus pontos de convergência com os demais setores econômicos e seu impacto nos desenvolvedores e fornecedores de insumos e serviços (GHOBAKHLOO, 2018; MARESOVA et al., 2018). Um caminho para a compreensão da direção que os investimentos podem tomar a curto prazo pode ser capturado ao explorar o que pensam os tomadores de opinião das grandes empresas que atuam e interagem com os elementos centrais da Indústria 4.0, sejam eles as tecnologias habilitadoras ou as novas estruturas e modelos de negócio provenientes da expansão digital.

Estudos focados em tecnologias específicas ou em integrações de tecnologias dentro do ambiente industrial também são presentes na literatura (MUHURI; SHUKLA; ABRAHAM, 2019; NAKAYAMA; DE MESQUITA SPÍNOLA; SILVA, 2020) e ganham importância conforme expandem-se e popularizam-se. Neste caso, a compreensão das particularidades de aplicação e como operacionalizar a transformação digital são assuntos centrais de discussão. Neles, destacam-se estudos de caso em diversas áreas, dentro (DAFFLON; MOALLA; OUZROUT, 2021) e fora (JAVAID et al., 2020) do ambiente industrial, assim como trabalhos exploratórios com foco nos desafios que a transição de tecnologia impõe sobre os já consolidados modelos de gestão industrial, como o *Lean Manufacturing* (TORTORELLA; GIGLIO; VAN DUN, 2019). Esses estudos focados tendem a enriquecer o conhecimento acadêmico sobre o significado da quarta revolução industrial em termos práticos, indo além das projeções e predições, olhando em mais detalhes os nuances das aplicações em ambientes tecnológicos reais.

1.2 OBJETIVO GERAL E OBJETIVOS ESPECÍFICOS

A presente dissertação visa explorar e melhor compreender as dificuldades associadas à adoção da Indústria 4.0 no Brasil, focando, em especial, no setor de manufatura. Como objetivo geral, a pesquisa gira em torno de analisar as principais dificuldades na transição entre os modelos de produção 3.0 e 4.0, compreender a priorização de investimentos a curto e médio prazo e quais desafios poderão ser enfrentados durante o processo transitório. Kagermann, 2013, argumenta que, ao mapear de maneira prévia as dificuldades e prioridades de um processo revolucionário, atua-se em prol de capitalizar os bônus e minimizar as perdas inerentes a ele.

Para atingir este objetivo, foram propostos três objetivos específicos: i) explorar o entendimento sobre o nível de prioridade e dificuldade na implementação das tecnologias habilitadoras nas empresas de manufatura do Brasil; ii) estudar os principais desafios, barreiras e dificuldades encontrados na migração de uma célula de manufatura 3.0 para uma célula 4.0, integrada; iii) discutir os resultados e correlações entre essas análises e traçar paralelos do contexto da I4.0 no país e em países com contextos similares.

Para tais, dois estudos foram conduzidos e serão apresentados na forma de artigos neste documento, de acordo com modelo alternativo homologado pela Universidade Estadual de Campinas e pela Faculdade de Engenharia Mecânica.

O primeiro trata-se de uma *survey* realizada com profissionais brasileiros de indústrias de manufatura que trabalham de forma direta ou indireta com a implementação de tecnologias habilitadoras da Indústria 4.0 em suas empresas ou em empresas parceiras. Essa pesquisa visa analisar o entendimento sobre o nível de prioridade e dificuldade na implementação de cada uma delas, à luz da literatura e em contraste com contextos econômicos e sociais de países similares ao Brasil.

O segundo estudo tem como foco explorar os principais desafios, barreiras e dificuldades encontrados na migração de uma célula de manufatura 3.0 para uma célula 4.0, conectada e capaz de tomar decisões de forma autônoma com base em dados, que interferem no próprio processo produtivo. O estudo propõe diretivas para auxiliar, em escala operacional de engenharia, projetos de conversão e melhoria de sistemas presentes em células automatizadas atuais. O segundo estudo foi desenvolvido em parceria com a escola SENAI de Campinas.

1.3 MÉTODOS APLICADOS

Para uma análise das interações entre o setor de manufatura do Brasil e as tecnologias habilitadoras da quarta revolução industrial, foi realizada uma pesquisa com os principais tomadores de decisão dessas empresas visando captar a percepção em relação ao grau de prioridade e de dificuldade na implementação dessas tecnologias. A *survey* foi conduzida de forma virtual, via *Google Forms*, conforme as boas práticas e recomendações da literatura para eliminação de vieses e do comitê de ética em pesquisa da Unicamp. Os respondentes foram selecionados a partir de bases como LinkedIn e demais agregadores de currículos, formando um grupo composto por tomadores de decisão, acadêmicos diretamente relacionados a empresas de manufatura, líderes e especialistas na área de automação, digitalização e ciência de dados, uma amostra não-probabilística por julgamento. Para cada tecnologia habilitadora selecionada da literatura, foi solicitado aos respondentes que classificassem em uma escala de 1 a 5 os níveis de prioridade e dificuldade para sua implementação, conforme suas experiências profissionais.

Posteriormente, foi utilizado um algoritmo de análise multicritério conhecido como *Fuzzy-TOPSIS* para ranqueamento das tecnologias habilitadoras nas duas dimensões estudadas. O caráter *fuzzificado* da análise de dados permitiu a modelagem da incerteza inerente às respostas obtidas e, a partir daí, realizar as discussões comparando com maior grau de assertividade ambas as dimensões analisadas na pesquisa. Essa foi a abordagem escolhida para a análise conjuntural, descrita em detalhes no artigo 1, denominado *"Industry 4.0 enabling technologies in manufacturing: implementation priorities and difficulties in an emerging country"*.

A seguir, o segundo passo da pesquisa foi explorar em detalhes como a aplicação dessas tecnologias pode ser realizada em uma célula real de manufatura, avaliando as principais dificuldades na conversão de uma célula 3.0 em uma 4.0, integrada e inteligente. Para tal, tomou-se como referência uma célula automatizada 3.0, presente no SENAI de Campinas, na qual foram estudados em detalhes cada um dos seus elementos, construindo modelos de estado atual e futuro para essa célula. A célula em questão é composta por um robô manipulador central que interage com um sistema de alimentação de peças (esteira), com um dispositivo de usinagem (fresadora e morsa) e com um aferidor de um parâmetro de qualidade selecionado (rugosímetro digital). Após modelada, foi proposta e colocada à prova uma sequência de atividades de atualização e integração dos componentes, além de adequação de *layout* e sequência de atividades, para tornar a célula autossuficiente na manufatura, na análise de qualidade e na realimentação dos próprios parâmetros de usinagem, com base em um algoritmo de aprendizado de máquina.

A partir daí, foram listadas cada uma das dificuldades observadas e superadas no processo de conversão, analisadas à luz da literatura e de outras experiências similares ao redor do mundo. Esta análise detalhada e operacional das tecnologias habilitadoras foi realizada e descrita no artigo 2, denominado *"Difficulties and challenges in the modernization of a production cell with the introduction of Industry 4.0 technologies"*.

1.4 OPÇÃO PELA APRESENTAÇÃO DA TESE EM FORMATO ALTERNATIVO

O presente texto é apresentado em formato alternativo, conforme homologado pela Universidade Estadual de Campinas e pela Faculdade de Engenharia Mecânica. Além das sessões introdutórias, a dissertação é composta por mais 3 capítulos. O capítulo 2 apresenta os dois artigos que compõem as pesquisas realizadas. Neste formato alternativo, os textos já submetidos e/ou aceitos em revistas internacionais compõem o corpo da dissertação. O Capítulo 3 propõe-se a apresentar uma discussão dos resultados obtidos em ambas as pesquisas, com o intuito de promover uma compreensão mais ampla do tema. Finalmente, o Capítulo 4 apresenta as conclusões e trabalhos futuros com base nos resultados discutidos.

2 ESTUDOS DESENVOLVIDOS (ARTIGOS)

O presente trabalho, como já descrito, é composto por duas pesquisas que visam, de forma complementar, explorar as principais dificuldades na adoção das tecnologias habilitadoras da Indústria 4.0 em sistemas de manufatura do Brasil. O texto apresentado a seguir trata-se de um artigo publicado no *Journal Technology Analysis & Strategic Management*. O segundo artigo é apresentado posteriormente, submetido a uma revista acadêmica de relevância internacional na área.

This is an Accepted Manuscript of an article published by Taylor & Francis in Technology Analysis and Strategic Management on 31 Mar 2021, available online: http://www.tandfonline.com/10.1080/09537325.2021.1908536

Industry 4.0 enabling technologies in manufacturing: implementation priorities and difficulties in an emerging country

ABSTRACT

Industry 4.0 is one of the most heterogeneous waves of global industrialisation and the impact of new technologies in industry is not clear. The present research aims to explore the perception of professionals from the Brazilian manufacturing sector regarding the main enabling technologies of Industry 4.0, their priority and difficulty level of implementation. A survey was carried out and collected data was analysed using a Fuzzy-TOPSIS approach. The results were summarised into a final ranking and it was possible to understand the perception of professionals regarding Brazilian manufacturing. For them, companies for aforementioned sector need to prioritize investments on shop-floor digitalization (common fact in developing countries) and focus on understanding cybersecurity requirements (which hinders the implementation process). Understanding of Industry 4.0 phenomena in emerging countries is essential to grasp its particularities at a global level, helping researchers, decision-makers, and policymakers to leverage Industry 4.0 in the context of a globalised economy.

KEYWORDS: Industry 4.0, manufacturing sector, emerging countries.

1. Introduction

Industry 4.0 is considered the new step-ahead of the global manufacturing system, with technological, social and economic implications (Beier *et al.*, 2020). Initially proposed by a German research group in 2011 (Kagermann, Wahlster and Helbig, 2013), the concept of Industry 4.0 has been changing over the years and absorbing some local characteristics in each of the world's markets (Culot *et al.*, 2020). This new stage of global industrialisation presents itself as disruptive, meaning it can change the way the world deals with industry in a definitive way, promoting changes to the foundations that support the current business context. Several studies point out that the effects of digital diffusion, such as broad Internet access, increase in the number of connected devices and new business models based on digital platforms will be responsible for deeply transforming modern societies and the way in which world is organised in different areas such as healthcare and epidemics (Aceto, Persico and Pescapé, 2020; Javaid *et al.*, 2020), social and environmental sustainability (Bai *et al.*, 2020; Ghobakhloo, 2020) and others.

Industry 4.0 (I4.0) can be defined as integration between physical systems of traditional manufacturing with totally cybernetic systems, responsible for making the intelligent management of the entire production chain in real time (Kagermann, Wahlster and Helbig, 2013). A wider definition is provided by the World Economic Forum: Industry 4.0 is a phenomenon in which several emerging technologies of the physical, digital and even the biological worlds converge together to drastically change the organisation of value chains globally, disrupting business models, reshaping production, distribution and consumption (Schwab and WEF, 2016).

In its current state, this fourth wave is transforming the production system into more autonomous and high-performance factories, capable of collecting, storing and analysing production data, known sometimes in the literature as Smart Factories (Osterrieder, Budde and Friedli, 2020). These factories have a full monitoring of their production process, with decentralised computing, capable of real-time adjustments of the entire production and supply chain (Sun, Yamamoto and Matsui, 2020), based on market demand, and also connected to the intelligent network that comprises it.

This revolution is affecting the manufacturing sector globally (Ghobakhloo, 2018; Tortorella and Fettermann, 2018). Tortorella and Fettermann, 2018, argue the importance to better understand how these technologies will be integrated in production systems. Several studies exist about the technology adoption process and the factors influencing it, including Sony and Naik, 2020. Despite diverse advances in this field, the literature lacks empirical studies mapping implementation priorities and difficulties in emerging countries, especially in Brazil. Understanding the adoption process in this context is important, since diverse emerging countries, and in particular Brazil, take part in major global supply chains, including food, automotive, aerospace, and other sectors. Many transnational companies are established in this country, needing to deal with specific adoption challenges.

Sony and Naik, 2020 present critical factors for I4.0 successful implementation. The digitalisation of processes in supply chain, concern with cybersecurity management and the commitment of upper management towards the fourth revolution are included in these critical factors. However, some barriers encountered by businesses for implementation, described by Schroeder *et al.*, 2019, are cultural barriers that can prevent the spread of ideas across the company structure, limited resources, and not knowing the best way to deal with generated data. Understanding how these barriers behave in an emerging market can contribute to better mapping the expansion of Industry 4.0 and to overcome barriers.

In this context, this study aims to analyse the Brazilian manufacturing segment regarding main Industry 4.0 enabling technologies and their adoption priorities and implementation difficulties. Two research questions are thus defined: Q1) Which enabling Industry 4.0 technologies need to be prioritised in Brazilian manufacturing companies in order to begin the transition for this new era? Q2) Which enabling Industry 4.0 technologies will present the greatest difficulty to be implemented? To answer them, this paper presents an exploratory study to evaluate the perceptions from experienced manufacturing professionals.

2. Theoretical background

2.1. Industry 4.0 in Emerging Countries

While part of the world moves towards the Fourth Industrial Revolution, greater is the gap between high-level automated industries and those that have not yet advanced according to these criteria. The World Economic Forum suggests that more digital work environments tend to cause changes in work relationships in different sectors of the economy (Schwab and WEF, 2016). Other studies (Caruso, 2017; Fareri *et al.*, 2020; Guzmán *et al.*, 2020; Pejic-Bach *et al.*, 2020) are being conducted around the world to debate issues related to Industry 4.0, such as the gap in professional training, human interaction with cyberphysical systems and emergence and disappearance of new forms of employment.

When observing markets on a geopolitical scale, developing and emerging countries, such as Brazil or India, should pay special attention to the expansion of new technologies and management models required in I4.0. Their current industrialisation model has some issues and may be considered a barrier to their competition at global level (Kamble, Gunasekaran and Sharma, 2018). In addition, developing countries generally present problems in internal capability and government regulation (Raj *et al.*, 2020). Therefore, it is important to conduct analysis in their industrial contexts, understanding their characteristics. Furthermore, comparison between developed and developing countries can offer important information for a broad understanding of how social and economic factors can influence the expansion of Industry 4.0 across the globe (Raj *et al.*, 2020). Recent researches that explored the main differences of I4.0 in emerging countries found out that lack of central articulation in the modernization initiatives of the industry and financial barriers in their markets are important points in this process (Bogoviz *et al.*, 2019). In addition, Bogoviz *et al.*, 2019, highlights that, in order to draw a meaningful context of developing countries, it’s necessary to understand the socioeconomic context of several nations.

When analysing the Brazilian manufacturing sector, it is possible to note that some performance indexes were reducing over the years (BCG, 2014) and one of the main reasons for this reduction is low productivity (Dresch *et al.*, 2018) undermining the companies’ competitiveness over the past few years. According to the Global Competitiveness Report, Brazil was in 71st place in the global ranking of competitiveness, presenting a drop when compared to previous years (WEF, 2019). Despite this, in terms of innovation level, Brazil is in the 40th position and will need to overcome some challenges to adopt Industry 4.0 concepts (WEF, 2019). According to reports from National Confederation of Industry (CNI, 2020), the Brazilian manufacturing sector is responsible for 11% share of the country’s GDP and 75% of all industrial production carried out mostly by large sized companies. However, when its contribution worldwide is analysed, Brazilian manufacturing industry has 1.8% in market share, much lower than China (24.8%) and the USA (15.3%).

Another challenge to overcome in Brazil is the level of education and professional qualification. According to the World Bank report (WB, 2019), the quality of basic and professional education in Brazil, based on international tests, has improved in recent decades, but it is still below developing countries with similar economies. In the context of Industry 4.0, high levels of education and employees' professional qualification are critical success factors. Studies indicate that the level of qualification of industrial players in the country is below the level present in developed countries for digital transformation, worsened by the economic crisis that Brazil has faced since 2014 (Cezarino *et al.*, 2019).

Finally, it is important to point out that Brazil has a central role in the economy of Latin America, which makes it stand out as an influential market in the region (CEPAL, 2018). Understanding the difficulties and priorities of the country's industry at the moment can mean an understanding of the region as a whole, given the similarities and economic cooperation between these countries. In addition, Brazilian literature has deeply explored the main technologies and concepts of the third industrial revolution, which provides a broad background for studies related to I4.0 (Neto *et al.*, 2015).

Unfortunately, to the best of our knowledge, the literature lacks several studies in Brazil, despite all these challenges. Contador *et al.*, 2020 explored the main opportunities and challenges in a general way, without focusing on enabling technologies, but allowing a broad understanding of the transition period to I4.0. Dalenogare *et al.*, 2018 explored the relationship between some enabling technologies of the Fourth Industrial Revolution in terms of contributing to the performance of the country's industrial processes, but without delving into the levels of difficulty in implementing each one. Finally, Tortorella, Giglio and van Dun, 2019 discussed how enabling technologies communicate with companies and their relation to the maturity of Lean Production. In addition, knowing that Industry 4.0 is a multi-disciplinary concept integrating several emerging technologies, these challenges may be even bigger.

2.2. Enabling Technologies in the Manufacturing Sector

The main Industry 4.0 characteristics can be separated into five categories: processes digitalisation; adaptive automation, focused on self-management of production systems; new interfaces between man and machine; new services and businesses with high added value, with emphasis on information management and protection; exchange of data and automated communication structures with high value (Kagermann, Wahlster and Helbig, 2013). Another point also highlighted in the literature is investment in data security and data privacy to protect platforms against attacks (Drath and Horch, 2014).

In terms of the main technologies, the Fourth Revolution will be guided by elements such as Internet of Things, Big Data, Cyber-physical systems, Machine Learning, Additive Manufacturing, Advanced Robotics and intensive use of simulated environments (Ahuett-Garza and Kurfess, 2018; Beier *et al.*, 2020; Culot *et al.*, 2020). These main Industry 4.0 technologies for manufacturing sector are shown on Figure 1.

A deeper understanding of the technologies and the interrelations between them is crucial to grasp the I4.0 phenomenal. The Internet of Things, for example, can be defined as a constant presence of computational elements in the most variable range of things and objects, such as sensors, actuators and smartphones, building a unified network, interacting and cooperating with each other to achieve common goals through the Internet (Lu *et al.*, 2015). Network of devices connected to the internet can enable the traceability of the value flow (products and data) in a supply chain (Zhong *et al.*, 2017). However, IoT can be implemented on its highest potential when associated with others enabling technologies, such as Cloud Computing (that consists of remote availability and access to computational resources, requiring only Internet connectivity, without physical hardware), RFID (Radio Frequency Identification) and Big Data Analytics. There are recent examples in the literature (Wang *et al.*, 2018) for the use of IoT-based platforms to measure the main key indicators for energy consumption of equipment and, thus, provide data for better resources' management within an industrial process.

Figure 1: Main enabling technologies of Industry 4.0 (Source: based on (Ahuett-Garza and Kurfess, 2018; Beier et al., 2020; Culot et al., 2020))

Big Data and Machine Learning are also closely related, once the first one is the background for a good Artificial Intelligence (IA) algorithm. Artificial Intelligence is a state of art in computer science and data analytics. Machine Learning corresponds to a varied set of IA algorithms capable of improving the results of future computations based on a database and previous iterations (Meng *et al.*, 2020). Autonomous robots can use IA-based systems to improve their behaviours, detecting the environment where they are, making decisions based on what they perceive/are programmed to recognize, and, finally, triggering a movement that results in an action (Harapanahalli *et al.*, 2019).

The process of transforming a less technological industrial age production floor into a much more digital, connected and information-filled industry is a combination of multiple technologies' implementation (Osterrieder, Budde and Friedli, 2020). The basic concept of shop floor digitalization proposes a new industrial model, reducing paper information and making processes more digital. Augmented reality, digital simulations, IoT and cloud storage are closely associated to a total digital shop floor. Nonetheless, cybersecurity is crucial to guarantee the information and secure the value that it contains, protecting the confidentiality, integrity and availability of digital data against any type of threat that may arise, especially when using the Internet or other types of shared networks (von Solms and von Solms, 2018). Building a cybersafe environment is pointed as one the main challenges of Industry 4.0 (Corallo, Lazoi and Lezzi, 2020).

Managers and decisionmakers on industrial organizations are the responsible to prioritize the investments to create this fully integrated environment. Having the knowledge of the potential of each enabling technology can be the key to more assertive decisions to avoid low return of investments during the beginning of this new industrial age. Enabling technologies are only true enablers if they generate value, working together in a connected cyber-physical environment.

3. Methodological procedures

To reach the results, five well-defined stages were carried out. Figure 2 presents these stages and they are detailed in the sequence.

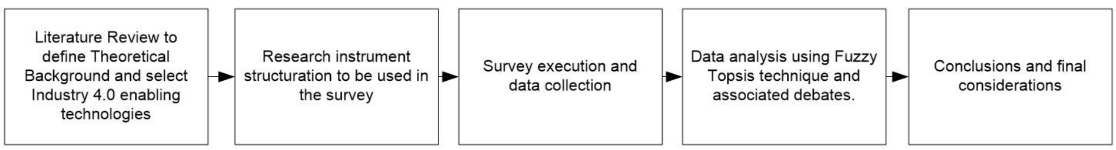

Figure 2: Stages carried out in the research (Source: authors)

The research began with a literature review (stage 1) in order to define theoretical background and select Industry 4.0 enabling technologies used to structure the research instrument (questionnaire). The scientific databases used were Science Direct, Scopus, Emerald Insight and Scielo, as well as Brazilian national economic reports. The research instrument for the survey was structured considering Industry 4.0 enabling technologies identified (stage 2), using similar surveys' models (Anholon *et al.*, 2018; Cielusinsky *et al.*, 2020). The questionnaire was approved by the university's research ethics committee and it was composed of two parts.

The first part was dedicated to sample characterisation. Two personal questions regarding the respondent was presented: a) activity sector of the company in which respondent works; b) years working/researching in the area. The second part presented 12 pairs of questions, each one related to one enabling technology, following standards presented in the literature (Kitchenham and Pfleeger, 2002). The questionnaire was carefully analysed among the authors, aiming to minimize unintentional bias in the elaboration of the questions. The final version of the questionnaire presents, for each technology, the same sentences to be evaluated in the same sequence of presentation to the respondents. The technologies, however, were randomly ordered in the questionnaire, minimizing the influence between them. Table 1 presents enabling technologies analysed and statements presented for them. Answers should be given considering a scale from totally disagree to totally agree. For each enabling technology, respondents must assess one statement related to priority and another one related to application difficulty.

The questionnaire was sent to professionals who have experience in Brazilian manufacturing sector, automation area and Industry 4.0 (stage 3). The sample was composed of companies' decision-makers, academics working directly with manufacturing companies, leaders etc. Possible participants acting in companies were identified through searches on professional network platforms (example LinkedIn), using terms "industry 4.0", "processes digitalization" and "improvement of manufacturing processes" to identify groups and profiles. For possible academic participants, the main source to find contacts was Lattes Curriculum Plataform (a Brazilian base with curriculum of researchers in different areas). Once again, the same terms were used to identify profiles of researchers in area.

The contact was made via e-mail or direct message and Google Forms platform was used for data collection and management, following recommendations from the literature (Kitchenham and Pfleeger, 2002) to ensure a higher response rate. Respondents were selected according to non-probabilistic sampling by judgment (or purposive) (Etikan, 2016), selecting the sample in order to best fit the criteria presented. This type of sampling is recommended for exploratory research, which aims to investigate new concepts, selecting a sample formed by experts in the sector. In total, they were sent to 114 candidates, with a response rate of 37.7%.

Table 1: I4.0 technologies and statements to evaluate

<table>
<tr><th>Technology</th><th>Question 1</th><th>Question 2</th></tr>
<tr><td>Cloud Computing</td><td rowspan="12">The technology mentioned, compared to the others, has a high level of priority in terms of implementation, so Brazilian manufacturing companies can start their journey towards the 4th Industrial Revolution.</td><td rowspan="12">Brazilian manufacturing companies, in general, will present many difficulties for the implementation of the mentioned technology.</td></tr>
<tr><td>Cybersecurity</td></tr>
<tr><td>Big Data Analytics</td></tr>
<tr><td>Internet of Things</td></tr>
<tr><td>Digital Simulation</td></tr>
<tr><td>Additive Manufacturing</td></tr>
<tr><td>Autonomous Robots</td></tr>
<tr><td>Shop floor Digitalisation</td></tr>
<tr><td>IA and Machine Learning</td></tr>
<tr><td>Augmented reality</td></tr>
<tr><td>RFID</td></tr>
<tr><td>Collaborative robots</td></tr>
</table>

In total, 43 valid responses were received. It is worth mentioning that the contact emails were sent only to professionals with guaranteed knowledge and experience in the area, ensuring greater quality and relevance in the responses received. Figure 3 shows the profile of respondents by specific area of activity in the manufacturing sector (graph a) and experience time (graph b). Companies' sizes, however, was not a decision variable to select respondents' profile. 44.1% of the respondents, based on public profile, has experience on large companies (more than 250 employees in the whole organization), 25.5% on medium-sized companies and 16.3% in small companies (less than 50 employees). 13.9% have partnership with multiple different sized industries. As mentioned above the article's focus does not lies in companies' sizes; however, we highlight the study of Masood and Sonntag, 2020, as an important research in Industry 4.0 implementation on small and medium enterprises. As already highlighted, the main focus of the sample was to select professionals in the Brazilian market capable of making a critical judgment of the sector as a whole and not specifically of the company in which the professional operates, as indicated by the questionnaire question.

The stage 4 is Data Analysis. The objective of this study, as previously described, is to find rankings of technologies related to priority and application difficulty. To rank items, a decision-support method stands out: TOPSIS, Technique for Order of Preference by Similarity to Ideal Solution (Marttunen, Lienert and Belton, 2017). TOPSIS is an ordering method that seeks to find alternatives in a decision matrix that are closest to a reference given as the best alternative (positive ideal solution, PIS) and most depart from an alternative given as worst (negative ideal solution, NIS). The distances to each of the ideal solutions are calculated and then synthesised in a proximity coefficient and the alternatives are then ordered according to those coefficients.

For the proposed problem in this study, a better approach is to use a variant of TOPSIS, known as Fuzzy-TOPSIS, with applications in several areas of the literature (Liu and

Wei, 2018; Palczewski and Sałabun, 2019). To fuzzify data, a triangular function was used as presented in Figure 4. In this figure, the given number on a sharp scale can be described as a triangular probability density function.

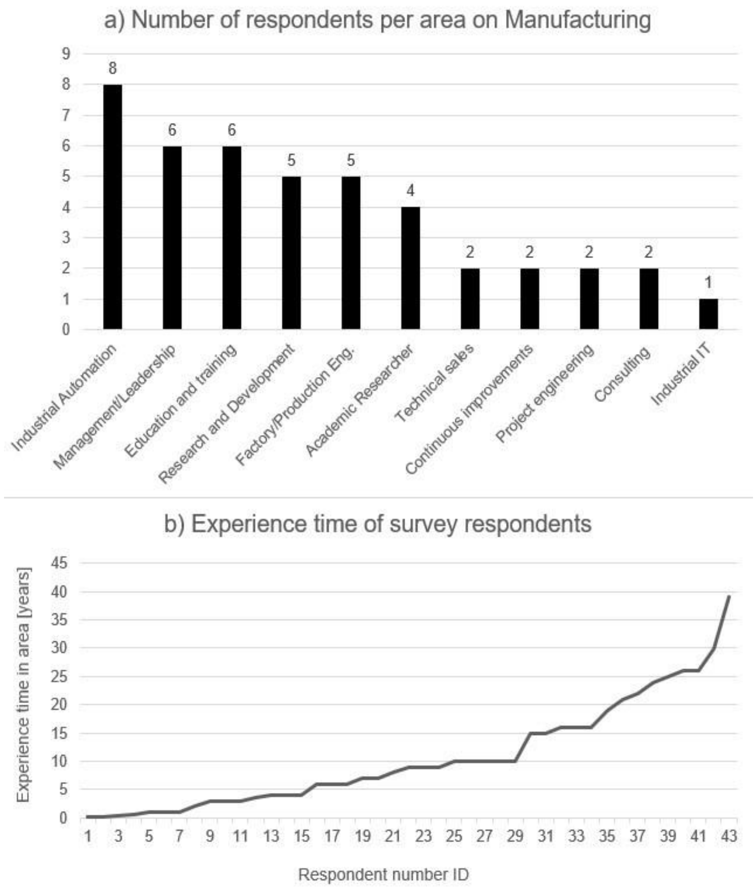

Figure 3: a) Number of respondents per specific working role inside manufacturing sector; b) experience time in the manufacturing area of each one of the 43 respondents

The diagram in Figure 5 represents the structure of the algorithm used for data analysis. For multicriteria analysis, some basic parameters must be defined, as described below:

- attributes: each one of the enabling technologies evaluated in the Survey;
- criteria: each respondent is a decision criterion; the final ranking is based on the answers given by each one;
- values of the criteria: the answers given by each respondent;
- weights of the criteria: respondent's months of experience in the manufacturing area were used as weights for the answers;

- PIS and NIS for Fuzzy-TOPSIS: the ideal solutions are given as the maximum (1;1;1) and minimum value that the answers can reach (5;5;5).

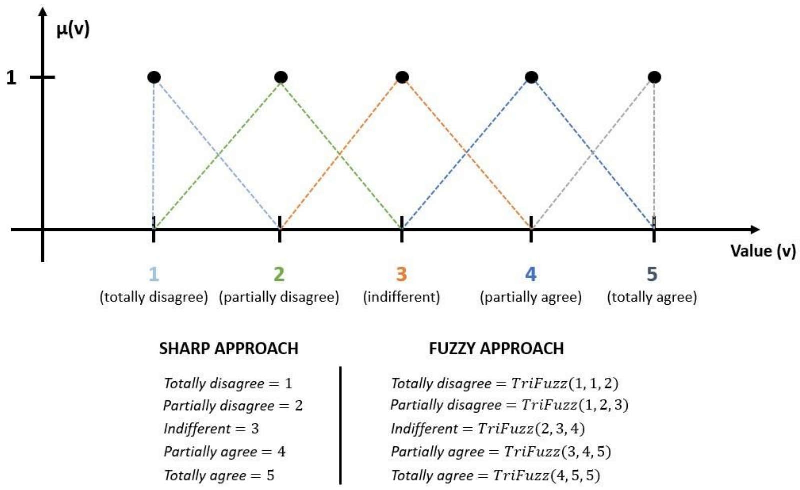

Figure 4: Sharp and Fuzzy approach scale (Source: authors)

The algorithm described in Figure 5 presents the computational structure to analyse the questionnaire data. Positive and negative ideal solutions as well as the questionnaire answers are fuzzified, and the fuzzy weights are applied to them. To guarantee the robustness of the responses, a sensitivity analysis is performed on the weights for verification. In this analysis, the weights will randomly fluctuate by 0-10%, thus checking the robustness of the ranking, i.e. whether the order varies with a slight fluctuation in weights. The two rankings obtained were discussed considering the literature, as presented next.

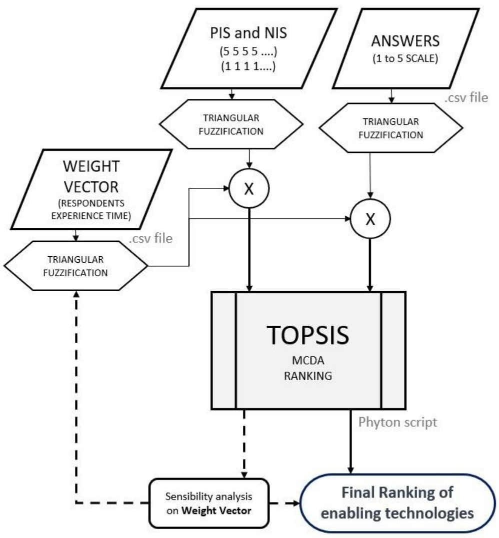

Figure 5: Algorithm model for data analysis

4. Results and discussion

The analysis of the data was performed using Fuzzy-TOPSIS algorithm described in Section 3. Two iterations were carried out for each level to evaluate priority for implementation of each enabling technology and difficulty associated to its implementation, considering Brazilian manufacturing sector context. For robustness check, a sensitivity analysis was performed on the applied weights; as reference, the TOPSIS method without fuzzification was used. Table 2 shows the final rankings for priority, using Fuzzy-TOPSIS (a) and TOPSIS Crisp, without fuzzification (b). Table 3 presents the same view for the difficulty levels.

The scores presented in Table 2 and Table 3 are the values generated internally by the algorithm to perform the classification of alternatives. When performing a sensitivity analysis of 0-10% of variation in weights, randomly, the Fuzzy-TOPSIS ranking for priority level had only minor changes (at most, one position change) between the central ranking values, while there were no changes in the ranking of the difficulty level, ensuring that the ordering presented is robust. It is also noted that there is only a small difference between the Fuzzy-TOPSIS ranking with the TOPSIS Crisp, however, it is worth pointing out that, as previously mentioned, using Fuzzy values as an approach makes a more realistic approximation of the uncertainty degree in the responses to the questionnaire, being a more coherent ranking with that expressed in the raw data.

Table 2: Results for data analysis algorithm with Fuzzy TOPSIS (a) and TOPSIS without fuzzification (b) on priority rate. The score shown is the final number TOPSIS algorithm uses to rank alternatives

a)	Technology	Fuzzy-TOPSIS Score
#1	Shop-floor Digitalisation	0.89471
#2	Internet of Things	0.85108
#3	Cybersecurity	0.81774
#4	Big Data Analytics	0.81299
#5	Cloud Computing	0.79757
#6	RFID	0.78569
#7	IA and Machine Learning	0.72875
#8	Autonomous Robotics	0.70509
#9	Collaborative robotics	0.69511
#10	Additive manufacturing	0.66071
#11	Digital Simulation	0.65430
#12	Augmented reality	0.60587

b)	Technology	TOPSIS Crisp Score
#1	Shop-floor Digitalisation	0.83373
#2	Internet of Things	0.81734
#3	Cybersecurity	0.76966
#4	Big Data Analytics	0.75452
#5	RFID	0.74471
#6	Cloud Computing	0.73838
#7	Autonomous Robotics	0.69005
#8	IA and Machine Learning	0.68218
#9	Collaborative robotics	0.66905
#10	Additive manufacturing	0.65533
#11	Digital Simulation	0.64501
#12	Augmented reality	0.61581

Table 3: Results for data analysis algorithm with FuzzyTOPSIS (a) and TOPSIS without fuzzification (b) on difficulty rate. The score shown is the final number TOPSIS algorithm uses to rank alternative.

a)	Technology	Fuzzy-TOPSIS Score
#1	Cybersecurity	0.80713
#2	Collaborative robotics	0.75799
#3	Big Data Analytics	0.75445
#4	IA and Machine Learning	0.73760
#5	Digital Simulation	0.67591
#6	Cloud Computing	0.66413
#7	Shop-floor Digitalisation	0.63911
#8	Autonomous Robotics	0.63583
#9	Augmented reality	0.56594
#10	Internet of Things	0.55644
#11	Additive manufacturing	0.55141
#12	RFID	0.37837

b)	Technology	TOPSIS Crisp Score
#1	Cybersecurity	0.75019
#2	Collaborative robotics	0.72085
#3	Big Data Analytics	0.70392
#4	Digital Simulation	0.64016
#5	IA and Machine Learning	0.63807
#6	Cloud Computing	0.61581
#7	Autonomous Robotics	0.59965
#8	Shop-floor Digitalisation	0.57713
#9	Additive manufacturing	0.52610
#10	Internet of Things	0.50064
#11	Augmented reality	0.48072
#12	RFID	0.36953

Results about the priority rate indicate that the shop floor digitalisation in the industrial processes is ranked first, aligned with the expectations detailed next. On the other hand, Shop-floor Digitalisation also appears only at the 7th position in terms of difficulty, which may reinforce the expected view that the accessibility of technology is not an issue.

According to some sources in the literature (Almada-Lobo, 2016; Hofmann and Rüsch, 2017) there is a certain confusion regarding the definitions of the enabling technologies and, due to this fact, the shop-floor digitalisation of process can be considered as less disruptive. According to the authors, a more digital shop floor is one the first steps of I4.0, seen as a natural step-ahead from the digital technologies already presented in the factories and, for some, also seen as the greatest revolution that I4.0 can drive. In addition, this result may point to a need for Brazilian companies to modernise their processes, since, for digitally mature systems, this technology should be well consolidated and, therefore, not present itself as an absolute priority. Due to the fact Brazilian companies are experiencing a low productivity level, according to national reports (CNI, 2020), the modernization and digitalization of industrial process may be a way to improve productivity. The Chinese evolution, pushing the "world factory" to a smarter and more technological manufacturing environment, overwhelm this lack of digitalization barriers (Beier *et al.*, 2017).

The IoT is ranked 2nd in the priority ranking, followed by Cybersecurity. IoT is very present in the literature, according to recent bibliometric analysis (Muhuri, Shukla and Abraham, 2019), in the specialised media and even in common media vehicles, which may justify its appearance among the main priority voices of companies. In addition, the low difficulty presented for this technology can place it in a position of high visibility among the exponents of manufacturing in the country. Another possible approach is that the Internet of Things has a broader scope than simply the industrial space, and it is present in people's daily lives, in wearables, mobile devices, Smart TVs, tablets, etc. Its popularity and the existence of successful cases with good results and return on investments may lead to higher priority for decision-makers. In EU, for example, the popularity and investments in IoT doubled or tripled in last 5 years (Statista, 2020). This example may inspire Brazilian companies, encouraging them to give more priority to IoT.

In the case of Cybersecurity, even though it presents itself as a technology with high priority, it also appears as a technology with a high level of difficulty, possibly making it the main bottleneck in Industry 4.0 adoption. This situation can be due to several factors, starting with issues companies may have to manage their data and then ensure information security. Data has gained more and more value within companies, and information management is increasingly important, which requires them to have a secure, fail-safe system to protect data as an asset within the factory. Literature in the cybersecurity area points out that costs associated with cybersecurity can present a challenge for manufacturing companies in developing countries (Leszczyna, 2019) and one of the most challenging barriers for Industry 4.0 in general (Corallo, Lazoi and Lezzi, 2020). It is important to mention that the respondents' profiles do not match with highly experienced IT professionals, with only one working directly with it. Based on it, the familiarity and experience that respondents have regarding this topic, in addition to the insecurity that a poorly protected system can cause to companies with confidential data, may have been an important factor for the position of this technology.

Not only the maintenance and implementation costs, but also costs associated with updating systems and defending against cybercrimes represent a significant portion of the budget for cybersecurity, without mentioning the required human capital, not so abundant in the labour market. Studies focused on challenges for a I4.0 adoption in emerging countries mention high investments and difficulty in training employees on digital skills on top 10 (Contador *et al.*, 2020). Despite all these difficulties, national (DSI, 2020) and international (EU, 2020) legislation regarding data security are forcing companies to prioritize cybersecurity even though it requires high effort and investment.

Big Data Analytics and Cloud Computing are two technologies that walk together on the development level, according to specialised literature, being a second step on the journey towards digitalisation and full connectivity of processes in the production chain. According to the results, both are in the middle of the priority ranking, illustrating part of this evolution in the roadmap for digitalising manufacturing processes (Ghobakhloo, 2018). However, they are at an intermediate level in difficulty, which puts them in a middle ground of viability. Based on this analysis of the data, both technologies can be better explored in future research and in the technology market as possible attractions for manufacturing.

The next technology in the priority ranking is RFID, one of the bases of I4.0 traceability, being a particular case in the country because it is already widely studied and more commonly applied in Brazilian industry, especially in logistics and in the control of goods and products along the supply chain (Pedroso, Zwicker and Souza, 2009; de Araujo Moretti *et* *al.*, 2019). This may be one of the reasons that makes it assume central position in the priority ranking and, at the same time, the last isolated position when measuring the difficulty level. This behaviour may be characteristic of technologies that are familiar and already applied, but with proven gains that prevent companies from discarding their expansion priorities.

AI and Machine Learning are central technologies in academic research in Industry 4.0, since they may provide the biggest disruptions in the way data and processes are treated, with impacts on employment and on the relationship with customers and team workers. For many decision-makers, they might be considered complex and without clear applications for manufacturing, even though it is one of the major turning points of the Fourth Industrial Revolution. It is possible that the survey results corroborate this view, since it maps Machine Learning and Artificial Intelligence within the top 5 most difficult to implement, but with little priority, which may be a sign of market distrust regarding assertive return of investment. In the same line already discussed, AI and ML can bring more return of investments when applied together with other enabling technologies. Some examples using AI on manufacturing contexts in developed countries, with higher levels of investment in I4.0, suggest that AI empowers IoT in a manufacturing environment (Shah, Wang and He, 2020; Tahsien, Karimipour and Spachos, 2020).

Finally, several technologies in positions 8 to 12 of the ranking are not (except perhaps by digital simulations) necessarily present in all types of companies, depending on market positioning, company size and growth strategy. Augmented Reality, for example, can be a connectivity enabler for remote maintenance between plants for large and medium sized companies, without the need for physical movement of professionals between them, saving time and decreasing problem-solving response time (Palmarini *et al.*, 2018). However, for small businesses, it is possible that applications like this will not be delivered with the same results and will not be prioritized by them. The same line of reasoning can be applied to the other technologies of this group, so it becomes plausible to group them in the last positions of the priority ranking.

5. Conclusion

The present study analysed the Brazilian manufacturing sector regarding main Industry 4.0 technologies adoption, considering priority for the implementation and their respective adoption difficulty levels. Survey data was analysed through Fuzzy-TOPSIS and some regional peculiarities were identified, such as the prioritisation of basic digitalisation technology at the shop floor level, which is expected for emerging markets, and the non-prioritisation of advanced technologies such as Machine Learning. Another important point raised is the implementation bottleneck that Cybersecurity may represent, considered of high priority but with high difficulty at the same time. Results suggest that there is room for a more robust IT infrastructure, but it requires more resources for implementation. In the short term, it can be expected investment to build a more connected and digitalized shop floor, with investments on basic I4.0 enabling technologies. In addition, building capabilities on

Cybersecurity, AI and Big Data Analytics can be expected from the manufacturing companies, as it is considered with higher difficulty in a context of initial development of I4.0.

The discussions presented here initiate an important debate on how manufacturing companies see the enabling technologies of Industry 4.0 within their business environment, which are the most prioritized technologies, bottlenecks, and barriers. Understanding the way different countries deal with the Fourth Industrial Revolution within their national context can be central to guide investments and government policies. This is a first step in emerging countries for local and world-class companies to better understand their context. In addition, these results complement other studies carried out in corporate management within this context of technological transition. In terms of theoretical contribution, the present study highlights comparatively more relevant themes to be focused on future research. In this way, become clearer and more pragmatic the scope of other studies.

Some limitations of this study are related to its method, which provides a partial view of the phenomenon. In addition, it is limited to the manufacturing sector of only one country. Future research may use the same approach in different countries, both in developed and developing markets and in different industrial sectors; thus, a direct parallel can be made between north and south. Another future research may look deeper into each one of the studied technologies, especially those of higher priority and difficulties or those identified as implementation bottlenecks. This would allow for the understanding of their particularities, thus proposing long and medium-term implementation solutions. In particular, difficulties associated to cybersecurity need to be better investigated in the Brazilian manufacturing sector.

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Difficulties and challenges in the modernization of a production cell with the introduction of Industry 4.0 technologies

1. Introduction

Since its first conception in Germany in 2011, the concept of Industry 4.0 has been diversified and expanded, with the introduction of new technologies and perspectives. According to Culot *et al.*, 2020, the first use of the expression Industry 4.0 in an academic publication dates from 2014, in an article of the manufacturing sector, and, from then on, there was a significant growth of publications on the subject. According to the same authors, more than 100 definitions of Industry 4.0 and its synonyms can be found in academic literature, reports from non-academic sources, as well as in specialized media (CULOT et al., 2020).

It is important to highlight that the concept of Industry 4.0 has been considerably expanded and has also been studied beyond the boundaries of manufacturing, including debates on economic (MARESOVA et al., 2018; SCHWAB, 2016) and social (FUKUDA, 2020) areas, due to the fact that the principles associated with the new revolution can provide profound changes in the organizational structures of global capitalism. One example is the idea of Society 5.0, first mentioned in Japan in 2016. It is a definition of a super connected and intelligent society, focusing on the interaction between human communities and the new technologies and perspectives coming from the Industry 4.0 (FUKUDA, 2020).

The fourth industrial revolution is a predicted transformation, as highlighted by Kagermann, 2013, which opens new possibilities and speculations, as well as opportunities for many exploratory researches, aiming to understand the particularities of the revolution in many spheres of society and in the productive systems.

Industry 4.0 was initially defined for manufacturing systems and many studies of I4.0 are focused on this area (CULOT et al., 2020), specially studies that analyse the transitions between 3.0 systems towards the new manufacturing models (NAKAYAMA; OF MESQUITA SPÍNOLA; SILVA, 2020). Among the aspects highlighted as central in this transition process, structural changes in the organization and in the production management are necessary for the entire manufacturing process to adapt to the new needs of technologies and integrated systems. It means starting from a centralized, complex and rigid structure, traditional in industrial organizations of the late twentieth century, towards a more modular and flexible industrial system, enabling expected levels of integration for an industrial system 4.0 (NAKAYAMA; OF MESQUITA SPÍNOLA; SILVA, 2020).

Kagermann, 2013 defines three levels of integration: 1) vertical integration between equipment and the manufacturing system in a single element of the chain; 2) horizontal integration, connecting the different elements of the chain and providing full traceability in industrial processes; and 3) end-to-end engineering integration, allowing highest level of customization on the production process, from end customers to primary suppliers.

Yin, Stecke and Li, 2018 also highlight significant changes in demand dimensions (variety, time and volume of production) in the transition from the third to the fourth revolution. In the case of variety, large-scale customization is a consumer trend that includes the customer needs in the production process since the beginning and it’s still not widely explored in the literature, mainly because it is a rising trend (JOST; SÜSSER, 2020). In the second dimension aforementioned, the short cycle time of the products pushes the production process towards a smaller *lead time,* making the high agility of the productive cells even more necessary. Finally, the volume dimension presents a high variability, with an increasingly oscillating demand due to the high customization (YIN; STECKE; LI, 2018).

A recent bibliometric study (KIPPER et al., 2020) points out that most of the challenges found and explored on the literature in recent years refer to the strategies of implementation and management of new technologies, focusing on the transitory processes between the current production model and intelligent and integrated systems. In this survey, Kipper *et al.* , 2020 highlights some challenges such as: lack of specific case studies to different contexts; questions regarding the necessary investments and expected return of them; barriers and difficulties related to the implementation of new technologies; transformation of traditional manufacturing systems considering new technologies; how Lean communicates with the new strategies of the 4.0 era (integration between Lean Manufacturing and the fourth industrial revolution is also widely explored in the literature of the area (ROSSINI et al., 2019; SHAHIN et al., 2020)). In addition, recent research indicates that the multiple levels of integration proposed by the fourth industrial revolution may fill some gaps left by traditional JIT production strategies, despite the imminent transformations in production cells and operational procedures.

Kagermann, 2013 defines as main aspect of the new industrialization era the presence of connectivity and data exchange between physical and digital elements, building an environment known as Cyber-physical System (CPS). Those systems are composed of intelligent machines, integrated to movement systems and storage of materials, in addition to the many other elements that are part of the industrial floor. After that the system becomes fully autonomous, capable of making decisions and performing actions based on the data captured and processed by the entire integrated system (KAGERMANN; WAHLSTER; HELBIG, 2013). According to Sanchez, Exposito and Aguilar, 2020, a fully autonomous production system must be able to perform three tasks, including monitoring of its own system, analysing data based on stored information and decision making that aims to optimize the production process.

The concept of cyber-physical systems has been complemented since its initial definition, with the new enabling technologies (DAFFLON; MOALLA; OUZROUT, 2021). Since then, numerous concepts have been added to the CPS scope, such as the pragmatic variants of the Internet of Things for industrial environments, additive manufacturing, cloud computing, artificial intelligence (AI) and machine learning, virtual and augmented reality, among other technologies (MUHURI; Shukla; ABRAHAM, 2019; QU et al., 2019). Talking about AI, algorithms can be applied in manufacturing processes (CARVALHO et al., 2019; FAHLE; PRINZ; KUHLENKÖTTER, 2020) to self-adjust and maintain the quality of the product, in addition to performing autonomous communication to the support areas (maintenance, quality control, logistics, etc.) aiming preventive action plans.

As mentioned by Kipper et al., 2020, one of the biggest challenges to be faced is the transformation of traditional manufacturing systems considering the new technologies. A plausible approach to understand the necessary transformations is characterized by the analysis of each subsystem that is part of the full industrial environment. Approaches related to individual technologies and the supply chain as a whole are more common in the literature (CULOT et al., 2020; DELPLA; KENNÉ; HOF, 2021), while manufacturing cell analyses are rare. Exploring the difficulties and changes in production cells in the transition period between industrial revolutions can be a new approach to have an overview of the industrial environment, in addition to possibly guide investments to manufacturing systems.

Through this scenario, the research aims to present the modernization process of a production cell, defined as the adoption of technologies associated with Industry 4.0, with a specific focus on the implementation of Artificial Intelligence and Machine Learning to I3.0 fully automated processes. The main challenges observed in this transition process will be reported and analysed, in order to contribute to professionals interested in the topic and future researchers. It is understood that by knowing some of the main difficulties that may occur in their projects, other professionals can act beforehand and optimize the process.

In addition to this introduction, which also contains a brief theoretical background, the article presents 3 more sections. Section 2 is dedicated to the presentation of methodological procedures, Section 3 to the presentation of results and debates, and Section 4, with conclusion and final comments.

2. Methodological procedures

To achieve the proposed objectives, the following steps (Figure 1) were performed.

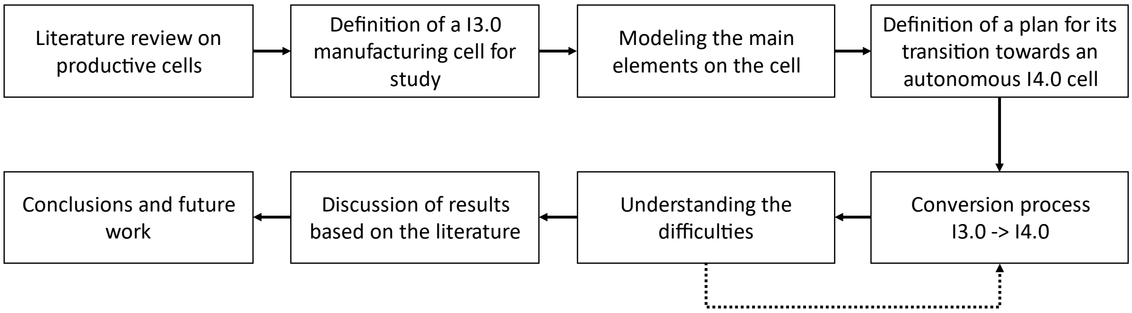

Figure 1 - Methodological approach for the present study

Initially, bibliographic research was carried out, aiming to build a theoretical background, using *Science Direct*, *Scopus*, *Emerald Insight*, *Scielo* and official reports referring to Industry 4.0. This research was important to map the concepts to be used in the study.

The automated cell 3.0 chosen for the study fits into the concept known as Robot-centred Manufacturing Cell (RCM), in which a manipulator robot presents itself at the centre of the production system and the other equipment is arranged around it (SHAIK; RAO; RAO, 2014). This arrangement, supported by reconfigurable robotic systems, with several manipulators and interface capabilities with different equipment (BI et al., 2008) presents itself as a predominant model in flexible cells, fully or partially automated during the third industrial revolution.

The focus of updating the studied cell is on implementing machine learning and artificial intelligence elements so that the system can be able to understand its own process deviations and, via data feedback, change the process parameters of the cell's manufacturing modules.

In addition to the manipulator system at the centre, the selected manufacturing cell has the following elements:

• Logistic loading system, such as a conveyor belt or gutter, in which the raw material for the process can be supplied to the cell.

• Manufacturing system, consisting of an element that will carry out some conversion operations in the input raw material. This process should generate a parameter to be measured later by a quality control system. In addition, the process must contain controllable parameters, such as cutting and feeding speed, etc., which can be varied later, impacting the quality of the final product.

• Quality control equipment, responsible for measuring a specific characteristic of the manufactured part. This element must be able to perform the measurement and to report the value of the measured quality parameter. The controlled parameter must be the direct implication of the manufacturing process.

• Central computer for processing, responsible for synchronizing cell activities. This computer can be dedicated for this control, as a Programmable Logic Controller (PLC), or a general-purpose computer with specific process synchronization platforms.

In partnership with the SENAI “Roberto Mange”, professional and technological training school in Campinas, an automated cell was mapped containing the aforementioned elements and which could be updated to its I4.0 version. The study cell belongs to a didactic structure present in the SENAI unit.

It was decided to use a didactic cell so that it would be possible to study each one of its components in details, without the need to interfere in a productive system in operation. In addition, SENAI is a centre of excellence in professional education in the country, several companies in the manufacturing sector use its structure for training, in line with the platforms used in the industrial units of these manufacturing companies. Finally, the work carried out will be able to serve as a platform for boosting Industry 4.0 in the region, due to the relevance of SENAI in training and professional qualification.

The diagram in Figure 2illustrates the initial structure of the selected cell for the study. In continuous lines, material flow through the cell; in dotted lines, information flow (control and positioning data).

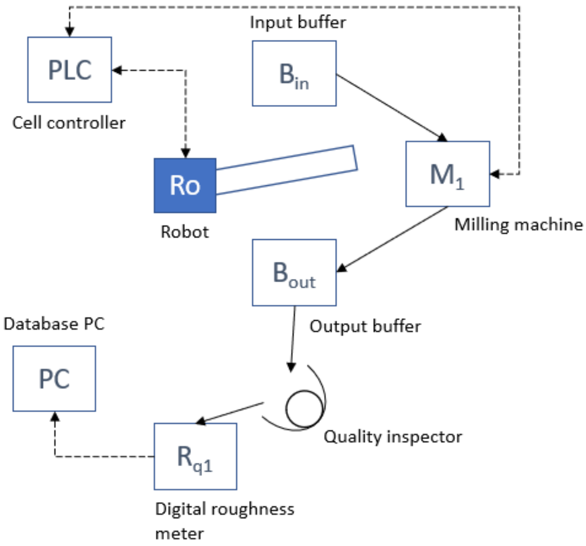

Figure 2 - Present state scheme of cell 3.0 selected for study

All the previous listed elements can be found in the diagram of Figure 2, for example, a machining device, whose operating parameters impact roughness, a quality parameter that is measured by the system. However, the automated cell does not have an integrated and connected product quality control system, thus a quality inspector is responsible for measuring the roughness. For the future state, the idea is to eliminate human action in the system and make the cell integrated, with feedback from quality parameters to process control. Figure 3 below shows the desired future state after the integration and implementation of an intelligent quality system, in addition to making the measurement data available in the cloud.

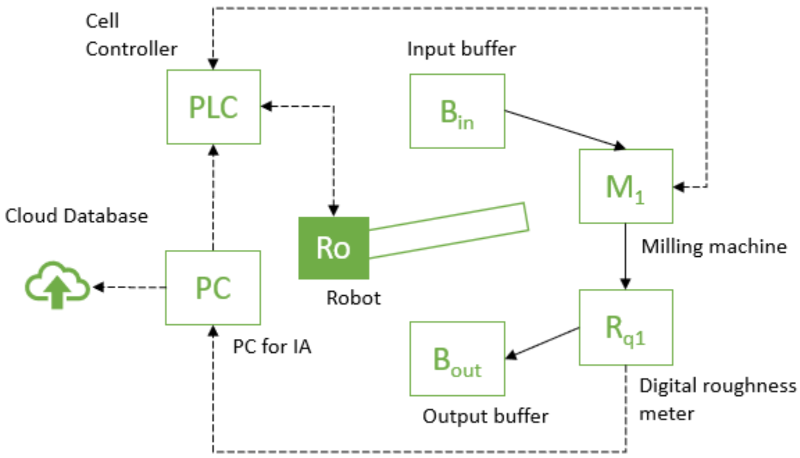

Figure 3 - Future state of the production cell 4.0

In the present cell under study, the central manipulator robot is a *Motoman SV3X*, model 2001, integrated with a *YASNAC XRC* controller also from *Motoman*. The robot's controller has an RS-232 serial data port for sending and receiving programs through a compatible computer, but it does not trigger inputs and outputs through this remote communication channel. In addition, communication can only be carried out between robot cycles, and remote interruption or data loading/reading during the execution of the cycle is not possible.

The machining element is a milling machine coupled to the end effector of the robot. The part to be machined is fixed to a pneumatic clamping system, whose opening and closing are electronically activated by the controller. The milling machine has a fixed rotation of approximately 1100RPM and cannot be varied without manual intervention by a specialized electrician.

The roughness meter present in the cell is a *MarSurf M300C* from the company *Mahr*, capable of printing physical roughness reports or sending them via USB communication to a computer, in text file format. The roughness meter has communication only for data reading, without the possibility of configuring measurement parameters remotely.

The next section presents the results and challenges found during the cell conversion process.

3. Results and discussion

Aiming a greater understanding of the manufacturing cell conversion process, exploring its challenges, Figure 4presents the steps taken from the initial I3.0 manufacturing cell to its complete integration into a I4.0 cell. Each numbered item on the diagram will be detailed and explored below.

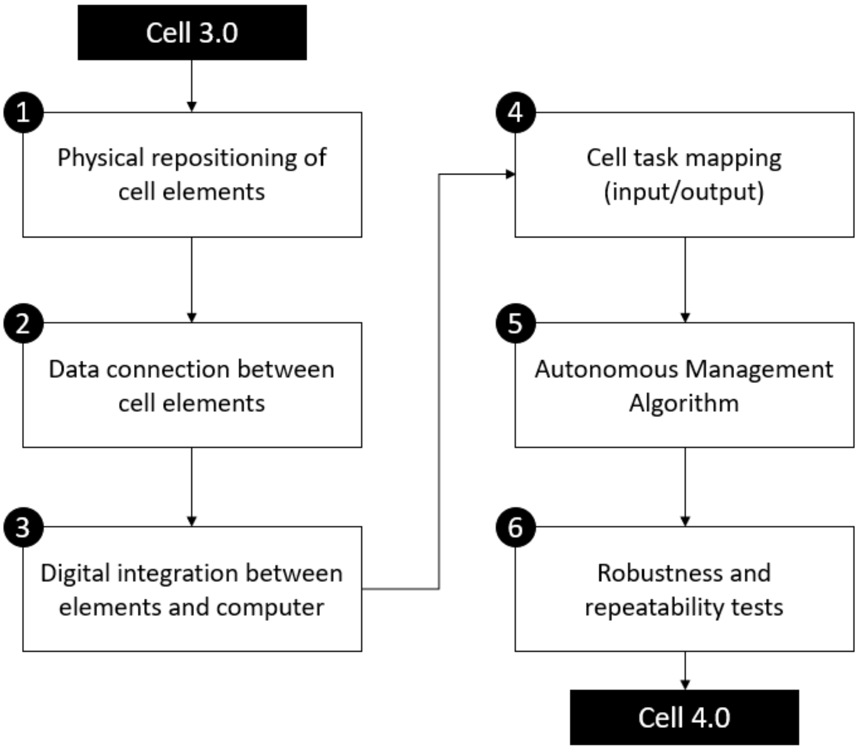

Figure 4 - Steps taken to convert a manufacturing cell 3.0 to 4.0

3.1. Step 1

First, it was necessary to map the physical elements of the cell and their spatial arrangement, in order to optimize and allow the interaction between them. Based on the model in Figure 3, it is necessary to arrange all the elements on the manufacturing cell in such a way that the interaction between the robot and the elements is simplified. At this stage, it was sought to integrate elements that were originally part of the cell, such as conveyors and the pneumatic vise (clamping), with elements operated by the quality inspector, in this case the digital roughness meter. In this integration, not all components are originally prepared to be operated in interfaces with the robotic manipulator, especially the digital roughness meter. To do so, it was necessary to adapt support elements for it, in a way that would allow its physical interaction with the robot, without impacting the correct functioning of the equipment.

Challenges with I4.0 cell layouts are obstacles present in the current literature on the fourth industrial revolution. According to recent research (FERNANDEZ-VIAGAS; FRAMINAN, 2021), layout difficulties in smart industries can be overcome with the use of learning algorithms that optimize the production flow within and between manufacturing cells. Other exploratory study (MORGAN et al., 2021) raised, among several elements, the design of the components of an intelligent factory as one of the challenges for the expansion of flexible and reconfigurable manufacturing systems.

Also, regarding to equipment, I4.0 integrated systems, like the one shown here, comprise equipment from different manufacturing areas (machining, electrical, pneumatics, metrology, etc.), which require the support of qualified professionals in each of them. If project group members do not have the necessary experience, there will be an important gap that can cost the project time and money to seek appropriate support. In the present case, the knowledge gap on the use of measuring equipment was the central barrier and the presence of an expert was necessary to understand the correct way of handling it, the way in which the final data are generated, and which data are relevant for quality analysis.

The training of project teams in Industry 4.0 is a challenge present in the literature and studied in different contexts (CHIARELLO et al., 2021). According to recent studies (KIPPER et al., 2021), it is possible to identify a trend of valorization in inclusive and multidisciplinary technological expertise, with greater interactions and partnerships with industrial environments, especially in the area of maintenance of digital systems (KANS; FIELDS; HÅKANSSON, 2020). The challenge of training and creating new skills is also reflected in new positions within the industry, with the creation of specialized positions for professionals who deal with integrated, intelligent and multi-connected systems (BENEŠOVÁ; TUPA, 2017).

3.2. Step 2

The second phase of the conversion is the preparation of each element of the cell to send or receive data, through a remote connection on an industrial network. At this stage, it was important to assess, for each cell component, 1) its ability to send data; 2) its ability to receive data; 3) its ability to be remotely triggered and monitored; 4) the timing of data transfer. Table 1 below presents the study carried out for the elements of the cell.

Some points stand out regarding the data flow between cell elements. First, as it is a I3.0 cell with equipment not originally prepared for real-time connectivity, it was impossible to create a single shared data management network, as they do not share the same communication protocol. Industrial OT networks and multifunction IT networks have different runtimes, which makes them substantially different for real-time task execution (LAUTENSCHLAEGER et al., 2021) and recent studies explore strategies so that it is possible to minimize the operation latency and make the integration between them in multiple input channels viable. However, studies show that systems with IoT-based structures must be adapted to work with data from different sources and, even if it requires more robust OT structures, be able to maintain the reliability and integrity of the data transmitted by it (EHIE; CHILTON, 2020).

Table 1 - Analysis of data flow through cell elements

	Send data (output)?	Receive data (input)?	Remotely triggered/monitored?	Timing?
Input buffer	Yes, presence sensor on the part inlet (digital)	Signal for conveyor drive (digital)	Yes, conveyor drive (digital);	Real-time
Milling Machine (pneumatic vise)	No	Signal for vise activation (digital)	Yes, vise drive (digital);	Real-time
Milling Machine (milling tool)	No	Signal for milling machine start (digital)	Yes, milling machine drive (digital);	Real-time
Digital roughness meter	Yes, file with measurement values (via USB)	Yes, command to start measurement (via USB)	No	After each measurement cycle
Robot	Yes, current program reading (via serial RS232 and Parallel)	Yes, program loading (via serial RS232 and Parallel)	No	After end of robot cycle
Computer (Windows PC)	Yes (USB, serial RS232 and Parallel Port)	Yes (USB, serial RS232 and Parallel Port)	N/A	Real-time

Another relevant point is the lack of communication adaptability and robust monitoring of elements in real time. The manufacturing cell robot, for example, is a *Motoman SV3X*, which features program transfer via parallel communication. This communication protocol is obsolete and not common in modern computers, which implies several difficulties in integration with serial and *Ethernet* protocols used in current industrial networks. These difficulties were overcome by setting up a local network, having a Windows computer as a centralizing and standardizing hub for data sources, and, from it, connected to an industrial *OT network* and to a cloud system, via the internet.

3.3. Step 3

Based on this, the third step in the digital conversion of the manufacturing cell was to prepare and integrate the central computer with the elements, so that it could serve its purpose as an integrative platform and AI processing centre responsible for managing the manufacturing cell. At this stage, it was first noticed that not all devices that made up the I3.0 cell had original support from their manufacturers, which is a frequent problem in companies with older automation systems. Similar cases in the literature (ZHAO et al., 2020) overcame these difficulties with the addition of external and connected devices that aimed to complement the limited capabilities of these devices.

In the case of the digital roughness meter, for example, the equipment manual did not present a clear guide on how to configure the communication between it and the computer, being necessary to search for alternative drivers, mandatory for its operation. As this is a general-purpose equipment, not provided by the manufacturer for real-time data transfer, the protocols for reading this information are not optimized for such use. It was up to the integration team to look for software alternatives to carry out the communication between the roughness meter and the database used by the artificial intelligence software that will process it.

Another important point to highlight is the presence of closed and dedicated software for each equipment, without open-source protocols that allow easy integration between them. In addition to the communication drivers, the files generated by the roughness meter have a dedicated format, that can only be opened by manufacturer-specific software. The necessary software, however, was not made available by the manufacturer with the equipment, making it necessary to search for applications capable of reading this data and converting it to text files in standard format. Without the correct conversion software, the device cannot export the data to the computer and, therefore, it is not possible to manipulate this information. The same challenge with the roughness meter is repeated with the milling system, as the program that controls the sending of machining parameters to the system is a dedicated manufacturer's platform, not allowing the integration of third-party software. In both cases, these digital systems were integrated using command macros via the operating system, which simulates operations by external users and allows the equipment programs to be used by third-party software.

Proprietary and closed source systems are challenges present in the literature that impact the conversion between I3.0 to I4.0 cells. Studies related to open-source frameworks highlight challenges in interconnecting fully open-source systems with systems that, even using similar approaches, create and remain restricted to a proprietary ecosystem (STOL et al., 2011). Other studies indicate that integrative solutions, hybrid systems or with open code, can be implemented with the help of intermediate platforms (or intermediate connection blocks) providing safer solutions and having robust platforms ensuring the integrity of information (PLAGA et al., 2019). A similar solution was the one adopted in the present study.

3.4. Step 4

The diagram in Figure 5illustrates the cell operation cycle, the reference for programming robot tasks and the PLC. At this stage, the programming of this cycle was carried out and the proposed operation was defined. To test the full functioning of the cell, a milling operation was defined in a polymeric part, so that it is possible to carry out the cycle tests in a usual operation in the industry, but with the possibility of failures without compromising the integrity of the components of the cell.

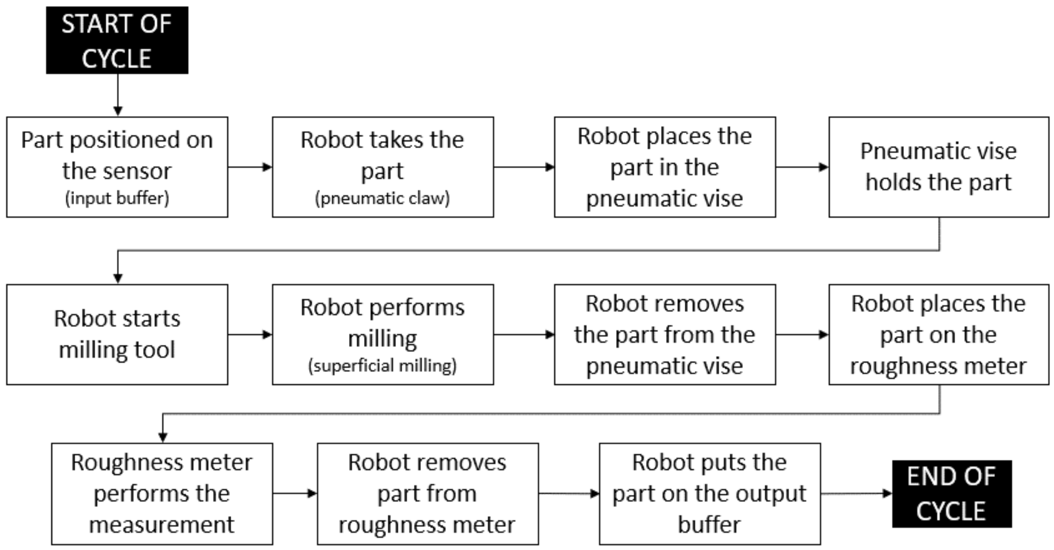

Figure 5 - Manufacturing cell operating cycle

At this stage, the focus of attention was the parameterization of the speeds and positions of the robot axes. Parameterization is important so that these values can be accessed and remotely changed by the AI algorithm responsible for cell cycle control.

3.5. Step 5

Intelligent control of a quality parameter is a central aspect of the proposed I4.0 cell. To this end, manual control was replaced by in-line measurement, with an artificial intelligence algorithm performing real-time data analysis and adjusting machining parameters in the robot program, allowing for its correction. The diagram in Figure 6shows the data flow of the AI algorithm for quality control.

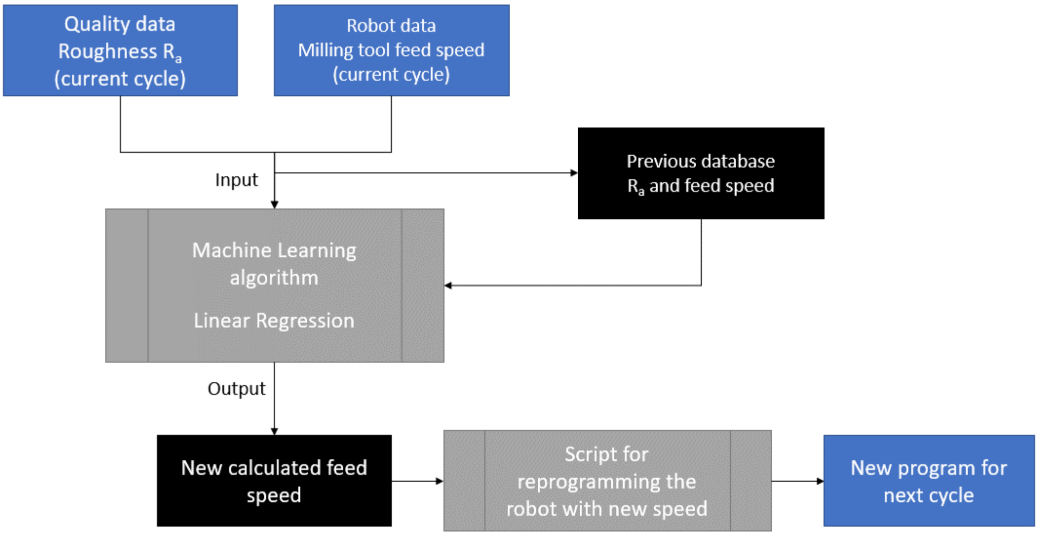

Figure 6 - Quality Control AI algorithm

According to the specialized literature (FELHO; KARPUSCHEWSKI; KUNDRÁK, 2015; Kumar, Kumar, ZINDANI; DAVIM, 2018), roughness parameter is linearly correlated with cutting tool feed in milling. The correlation factor between these two variables can be estimated based on a measurement history and the machine learning algorithm can be responsible for estimating and calibrating the curve at each cell operation cycle. For the present activity, the algorithm was developed in *Python*, with the help of open-source libraries for data management and support with machine learning.

The algorithm performs the following operations: 1) it reads the current program from the robot's controller system, in particular the tool feed value at the time of machining. It is worth noting that the speed unit, which is inserted in the robot program, is related to the relative speed between the axes, but there is no reference in the literature that directly describes this relationship with the roughness value, which makes a learning algorithm even more needed; 2) reads from the roughness meter the roughness value *Ra* generated after the operation; 3) the historical values are added to the new measure; 4) the learning algorithm is run, followed by the prediction algorithm, which outputs the best feed speed to reach an optimal roughness value. For the tests, the specification value was defined arbitrarily; 5) the program is reloaded on the robot to start the new cycle.

The complete execution of the algorithm takes about two seconds, with a database of 50 measurements.

At this stage, the challenge of optimizing the algorithm to run it in such a way as not to delay the execution of the robot cycle stands out. According to the literature, cycle time optimization is a fundamental aspect to guarantee the efficiency of a cell with robotic manipulators and there are several modelling techniques for cycle optimization (SPENSIERI et al., 2021). Ensuring the optimization of robotic systems can be an even greater challenge for systems that need to be more responsive, such as collaborative robots, in which reaction time directly impacts safety (YU; Huang, Huang, CHANG, 2021).

Another challenge to highlight was the integration between dedicated and proprietary software with open-source systems. In the present case, the Windows platform allowed greater integration via system commands, which could be more complex to be done on other platforms. As already described in previous steps, this is a very present challenge in cell conversion that can have a direct impact on data security, and more attention should be paid when data integrity can directly compromise the functioning of a physical system, such as a robotic manipulator. (LEZZI; LAZOI; CORALLO, 2018; PLAGA et al., 2019)

3.6. Step 6

The biggest limitation that differentiates an I4.0 didactic cell from a real cell is its level of robustness and the need to guarantee repeatability. A challenge regarding this cell is the guarantee that the equipment has backups in case of failure. In this case, there was no other similar equipment to the measurement system used, especially one that had digital data output for external processing of information, limiting the project to the equipment described above. The other roughness meters existing in the plant were of lower technology, not being viable options for the proposed cell. This limitation opens a discussion about the level of technology and spare equipment in case of breakdowns or issues during the production process.

The issue of obsolescence is something discussed in the literature and plays an important role in the transition from I3.0 to I4.0 systems. Studies conducted in China (ZHAO et al., 2020) pointed out the need to adapt CNC manufacturing systems to integrated systems, upgrading their main connectivity functions, while maintaining their original physical structure. It is worth pointing out that even solutions like the one presented above can still present challenges in the cybersecurity area, one of the pillars of Industry 4.0, in an attempt to update devices not prepared for it (GOURISETTI; MYLREA; PATANGIA, 2020).

4. Conclusion and future work

This research has as main objective to explore a transition process between a manufacturing cell with elements of Industry 3.0 to an autonomous management cell 4.0. The main challenges and difficulties at each stage of the transition were discussed and elucidated with similar experiences in the literature. As a central discussion, the difficulties in carrying out the integration of systems not prepared for connections in industrial networks, proprietary software and aspects of robustness and obsolescence stand out. Another important point highlighted was the training of the systems integrator team, which must be composed of people with different experiences and skills, necessary to ensure fluidity in the conversion process.

It is important to highlight that the transformation steps performed in a didactic cell can be applied in an industrial cell, on a larger scale, and it is expected that the challenges related to cell technologies are similar. In an industrial cell, aspects such as technology conversion time and robustness gain greater relevance, so it is a future opportunity to study the same exploratory procedure in different industrial cells. Finally, it was possible to clarify the understanding of the main difficulties encountered in the migration between systems and provide an initial overview for further studies of the individual elements present in manufacturing systems.

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3 DISCUSSÃO

O primeiro artigo apresentado teve como resultado principal dois rankings gerais de priorização e dificuldade que, munindo-se da visão de profissionais atuantes no setor de manufatura no país, ilustram o contexto atual da implementação das tecnologias habilitadoras da Indústria 4.0. O segundo artigo explorou o microcosmo formado por uma célula de manufatura e quais as dificuldades encontradas na implantação das tecnologias habilitadoras para torná-la autônoma e inteligente. Segundo Schwab, 2016, compreender a quarta revolução industrial como um fenômeno global é, também, compreender as particularidades que as novas mudanças tecnológicas impõem sobre as diferentes sociedades.

Os resultados obtidos no primeiro estudo demonstram um alto grau de priorização na inserção de elementos digitais no chão de fábrica da manufatura. Conforme discutido em detalhes no artigo, esse resultado pode ilustrar como a transformação digital no contexto de países em desenvolvimento, o primeiro passo rumo à Industria 4.0, ainda possui relevância, em contraste com países que já possuem uma base instalada digital em suas operações e podem priorizar tecnologias que dependem de infraestrutura, como *IoT* e IA. Além disso, pode-se potencialmente indicar uma carência das tecnologias digitais que compõe a base da I4.0, que tende a se apresentar como um obstáculo econômico adicional em contextos de menor investimento e menor inserção tecnológica no mercado

Schuh et al., 2017, em estudo publicado pela Acatech da Alemanha, sugere uma forma de medir o grau de maturidade de um sistema produtivo no processo transitório entre a terceira e a quarta revolução industrial, com base na infraestrutura e tecnologias aplicadas no processo. Nessa avaliação de maturidade, o processo deve estar digitalizado e conectado como premissas e pré-requisitos para a I4.0. Apenas quando os dados gerados nos elementos do processo se tornam computáveis, visíveis ao próprio processo e transparentes aos demais elementos da manufatura que pode-se considera-lo como um sistema 4.0.

A dificuldade de trabalhar com equipamentos e sistemas de medição e transformação obsoletos, não preparados para um ecossistema cyber-físico, mostrou-se presente no segundo estudo, sendo uma importante barreira discutida e potencialmente difícil de ser superada sem investimentos. Compreender esses desafios práticos na digitalização e integração completa de sistemas de manufatura 3.0 pode ser uma importante ferramenta para compreensão de como tornar prática essa priorização, especialmente para tomadores de decisão.

Em contrapartida, soluções com menores investimentos, como as soluções empregadas no estudo da célula 4.0, podem apresentar-se como mais vulneráveis a problemas ou ataques que comprometam a integridade dos dados. Cibersegurança, como apresentada no topo do ranking de dificuldade, é um desafio claro para o setor de manufatura e não pode ser negligenciado, conforme apontado em diversos estudos na área (LESZCZYNA, 2019; LEZZI; LAZOI; CORALLO, 2018). Sistemas integrados com tecnologias obsoletas ou não adaptadas para serem compatíveis com as boas práticas de segurança digital podem potencialmente apresentarem-se como elos vulneráveis na cadeia de informação na indústria. O processo de transformação da célula 3.0 parece apontar que protocolos não padronizados de comunicação e elementos de integração não dedicados podem estar entre esses pontos de vulnerabilidade de sistemas 4.0 em condições similares ao do estudado. Não obstante, plataformas *IoT*, vistas como prioritárias nas indústrias de manufatura, dependem de equipamentos atualizados, seguros e que possuam as corretas interfaces de comunicação para gerar valor no processo produtivo sem apresentar riscos.

Outro ponto que se apresenta latente nos resultados dos estudos apresentados é a necessidade de uma equipe multidisciplinar e capacitada nas principais tecnologias da quarta revolução industrial para que as principais barreiras encontradas possam ser superadas de forma produtiva em um contexto industrial. Os resultados do segundo estudo mostraram que células similares a estudada requerem profissionais com diversas competências nas tecnologias habilitadoras da I4.0 e que isso pode ser um possível ponto de atenção para os tomadores de decisão, especialmente quando as tecnologias avançadas da quarta revolução industrial não apresentam-se como prioritárias para os gestores industriais na manufatura.

Finalmente, o estudo conduzido no segundo artigo tende a indicar que é possível gerar valor ao processo com aplicações simples de IA, como algoritmos de regressão ou redes neurais de poucos níveis, especialmente em análise de sistemas com um número restrito de variáveis ou com comportamentos mais conhecidos. Isso potencialmente vai de encontro ao nível de dificuldade de implementação observado no primeiro estudo, indicando uma possível necessidade de aprofundamento no conceito de inteligência artificial e nos possíveis ganhos que é possível obter a partir dela em processos de manufatura.

4 CONCLUSÃO E TRABALHOS FUTUROS

A Indústria 4.0 apresenta-se como um tema central nos estudos contemporâneos da Engenharia de Produção e Manufatura, tendo expandido de forma significativa sua presença em periódicos científicos, conforme apontam levantamentos bibliométricos (KIPPER et al., 2020). A abordagem proposta nos dois artigos apresenta uma forma de se explorar, de maneira pragmática, as implicações conceituais levantadas com base em economias desenvolvidas para um país em desenvolvimento, como no caso do Brasil. Partindo de uma visão mais ampla, foi possível traçar um panorama geral dos graus de prioridade e dificuldade de implementação das tecnologias habilitadoras da quarta revolução industrial na manufatura do país, expandindo para outros contextos similares em países em desenvolvimento. A seguir, foi operacionalizado o processo de conversão de uma célula 3.0 para 4.0, levantando as dificuldades de implementação de forma mais específica e, à luz da literatura, investigado a fundo como superar cada desafio apresentado. Com isso, foi possível explorar a Indústria 4.0 em suas diferentes escalas: priorização em uma perspectiva executiva e implementação com uma perspectiva operacional.

Os trabalhos aqui descritos e apresentados são mais um passo nos esforços de compreensão do fenômeno da Indústria 4.0 no Brasil e podem servir como referência para possíveis trabalhos futuros na área. Na prática, os resultados obtidos podem servir tanto como um direcionamento para empresas do setor que desejam compreender melhor o caminho a trilhar rumo a uma fábrica inteligente, quanto para times de pesquisa que buscam se aprofundar em tecnologias ou aspectos particulares da quarta revolução industrial. Os rankings obtidos de priorização e dificuldade de implementação das tecnologias podem servir como referência no direcionamento do mercado em relação aos avanços tecnológicos do setor e direcionar de forma pragmática os futuros passos daqueles que se propõem como agentes ativos de transformação da indústria. De forma mais operacional, o estudo de conversão da célula 4.0 apresenta uma sugestão de passo a passo estruturado de referência, que pode ser utilizado como ponto de partida para trabalhos industriais e pesquisas acadêmicas em diferentes contextos de transição de tecnologias na área de manufatura.

Vale destacar que algumas limitações desse estudo são relacionadas aos métodos utilizados, que analisam e exploram um recorte parcial de um fenômeno amplo, com particularidades a serem exploradas. Além disso, a pesquisa se resume ao setor de manufatura brasileiro. Outro ponto de limitação é a estrutura da célula de manufatura analisada, com suas características próprias e detalhadas no artigo 2.

Como trabalhos futuros, sugere-se a implementação de metodologias similares em diferentes contextos sociais e econômicos, com a finalidade de compará-los com o contexto atual da manufatura brasileira. Outra sugestão é a aplicação do método de conversão de células 3.0 para 4.0 em diferentes processos industriais, explorando as semelhanças e particularidades entre eles. Finalmente, destaca-se que o conjunto das tecnologias habilitadoras da Indústria 4.0 é algo em constante transformação e novas ferramentas se incorporam de tempos em tempos a essa lista. Por isso, sugere-se também a expansão dos estudos realizados após alguns anos ou após uma possível mudança maior no contexto industrial do país, de forma a compreender como novas tecnologias são encaradas nesses novos contextos. *Blockchain*, canais de comunicação 5G, veículos autônomos e teleguiados são exemplos de tecnologias que não foram englobadas no contexto das pesquisas aqui apresentadas e discutidas, mas que podem ser incorporadas a trabalhos futuros, seguindo o mesmo modelo aqui apresentado.

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