Archisman Sen

INDUSTRY 4.0 AND COMPUTATIONAL VISION: AN APPLICATION BASED CASE STUDY AT FABRICA DO FUTURO AT USP

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Trabalho De Formatura Apresentado À

Escola Politécnica Da Universidade De

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Orientador: Prof. Dr. Eduardo de Senzi Zancul

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To each and every person who motivated,
and helped me to work at Fabrica do Futuro.

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“I never teach my pupils;
I only attempt to provide
the conditions in which they can learn.”
(Albert Einstein)

ABSTRACT

Industry 4.0, is the talk of the next higher level value transition of the industry and how various activities in this context are being carried out has magnanimous significance in the very rapidly evolving and changing global production scenario. The faster the current industries operating in a traditional way catch up with the oncoming inevitable change would have a better competitive edge.

In order to have a faster pace of research and implementation of the practices and techniques necessary towards this migration, major portion of big-brand companies have started to invest heavily, not only through developing in-house capabilities and methods, but also having a close interaction with university professors, students and utilizing the research labs in these institutions to have a better insight and also a smooth transition of knowledge and know-how and personal, at a cheaper investment. Thus, many universities in different parts of Europe, Asia, US, and Latin America are emerging out to be pioneers in supporting this activity through a high investment, research and setting up of excellence centres, generally termed as Learning Factory for Industry 4.0.

In the wake of this global development, in this work we go through a broad outlook on what is Industry 4.0, what are its primary elements, also often termed as Key Enablers, while the focus would be on the study of Computational Vision and application of the same in the Fabrica do Future for demonstration of a smart assembly line having lean manufacturing processes.

At the University of Sao Paulo, within the Department of Production Engineering, a project for the establishment of a Learning Factory is on course through the support of multiple industry partners, this paper focuses mainly on the implementation of Computational Vision in this workspace.

Keywords: Industry 4.0, Lean Manufacturing, Learning Factory, Fabrica do Futuro, Computational Vision, Virtual Reality, Augmented Reality

RESUMO

A indústria 4.0 é o próximo estágio na evolução industrial. Atualmente, há intensa discussão sobre a próxima transição de valor de alto nível da indústria e como diversas atividades nesse contexto estão sendo desenvolvidas tem grande significância no cenário global de produção dinâmico e em rápida evolução. Quanto mais rápido a indústria atual, operando de maneira tradicional, alcançar a mudança inevitável que está por vir, maior a sua vantagem competitiva.

A fim de ter uma pesquisa mais rápida e a implementação das práticas e técnicas necessárias a essa migração, grande parte das empresas de renome começaram a investir consideravelmente, não apenas através do desenvolvimento de capacidades e métodos internos, mas também através de cooperação intensa com universidades e utilizando os seus laboratórios de pesquisa e mão-de-obra especializada. Portanto, muitas universidades em diversas partes da Europa, da Ásia, dos EUA e da América Latina estão surgindo como pioneiras no apoio dessa evolução por meio de tecnologia ou fundos, para pesquisas profundas em todos os aspectos desse tema e organizando centros de excelência, geralmente conhecidos como Fábrica de Aprendizado para a Indústria 4.0.

Com o advento desse desenvolvimento global, neste trabalho apresentamos uma visão geral da Indústria 4.0, quais são seus elementos essenciais, conhecidos como *Key Enablers*, enquanto o foco seria em um estudo de Visão Computacional e sua aplicação na Fábrica do Futuro para demonstração de uma linha de produção inteligente, tendo elementos como processo de produção enxuta e sua aplicação na montagem de um skate conectado. Neste projeto, apenas uma parte das possibilidades da Visão Computacional foi utilizada e também foi delineado o escopo de possível evolução da linha de produção.

Palavras-chave: Indústria 4.0, Produção enxuta, *Learning Factory* (Fábrica de Aprendizado), Fábrica do Futuro, Visão Computacional, Realidade Virtual, Realidade Aumentada

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LIST OF ABBREVIATIONS AND ACRONYMS

ABII	Associação Brasileira de Internet Industria
ABIMAQ	Associação Brasileira da indústria de Máquinas e Equipamento
ACA	Adaptive Clustering Algorithm
ACE	Allowance for Corporate Equity
AMP	Additive Manufacturing Processes
BCG	Boston Consultancy Group
BDA	Big Data Analytics
CA	Conveying Agents
CAD	Computer-Aided Design
CAx	Computer Aided Processes
CBDM	Cloud-Based Digital Manufacturing
CMM	Coordinate Measuring Machinery
CNI	Brazil's National Confederation of Industry
CNN	Convolutional Neural Network
CIM	Computer Integrated Manufacturing
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
CV	Computational Vision
DBDDAS	Dynamic Big Data Driven Application Systems
DDM	Direct Digital Manufacturing
DL	Deep Learning
DTAM	Digital Thread for Additive Manufacturing
ERP	Engineering Resource Planning
FF	Fabrica do Futuro
FPGA	Field Programmable Gate Array
GMM	Gaussian Mixture Model

GPS	Global Positioning System
GPU	Graphics Processing Unit
I4.0	Industry 4.0
ICT	Information and Communications Technology
IMS	Intelligence Maintenance Systems
IoT	Internet of Things
MA	Machining Agents
MES	Manufacturing execution systems
M-CPS	Manufacturing Cyber-Physical System
MLP	Multilayer Perceptrons
MVISIA	Máquinas de Visão e Inteligência Artificial
OEE	Overall Equipment Effectiveness
PHM	Prognostics and Health Management
RFID	Radio-frequency Identification
RNN	Recurrent Neural network
ROI	Return On Investment
RUL	Remaining Utilization Life
SA	Supplementary Agents
SCM	Supply Chain Management
SME	Small and Medium Scale Enterprises
SOM	Self-Organizing Map
TPS	Toyota Production System
TQM	Total Quality Management

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1 INTRODUCTION

Industry 4.0 (I4.0) is about synchronized integration of the components of the digital and physical worlds of manufacturing. In here, every manufacturing elements trigger actions and control themselves independently based on the control and feedback commands/information, which are autonomously exchanged to and from the digital world or a model replica of the physical system to which it is being linked to. For this, the requirement is that of small decentralized and digitalized production networks that are independent of human intervention and autonomously act to control their operations depending on their environment changes and requirements. Although there is quite some difference between what the real form of Industry 4.0 would look like, there is a consensus about the main aspects of future manufacturing vision, which are: (1) Smart Factory; (2) Smart Products; (3) Business Models; and (4) Customers. This concept was given by initially given by Qin et al. (2016), however, was further elaborated by Pereira and Romero (2017).

Industry 4.0 is a new manufacturing paradigm that is focused by large towards the utilization of smart techniques of automation and digitalization of production processes for the creation of smart products and processes. This process of using multiple through a complete transformation of conventional manufacturing systems. And one of the main key players to help in achieving this successful operation of the Industry 4.0 is Cyber-Physical Production System (CPPS).

Smart Factory comprises of manufacturing solutions and a close-knit integration of automation and digitization by using configurable structures and tech-heavy solutions, which are mostly ICT based. This approach enhances real-time monitoring with the help of sensors and actuators. Smart factories, in general, are considered to be more efficient and also much oriented to the complex needs of the market.

Smart Products are Big Data based self-monitored autonomously handled while being integrated with the whole value chain actively, thus creating traceability for the product throughout its lifecycle. Furthermore, smart products, as final products should also be traceable using lifecycle monitoring. Some of the major features of Smart Products are in conjunction with capability, data storage, communication and interaction with an in-built sophisticated environment. This ambience leads to the gathering of continuous data from the product which in turn helps us to make the system of a continuous improvement one, like a self-controlled Lean system.

Business Models are being highly influenced by Industry 4.0 since this new manufacturing paradigm implies a new way of communication along supply chains. Business modelling has been changing in the last few years due to new industrial and market requirements and new models which are emerging, are allowing the creation of collaborative environments or synergies of various inter- and intra- related sectors. There are many opportunities for optimizing value creation processes and integration through the value chain, in order to achieve self-organization capability and real-time integration and communication.

Customers play a major role, in every business model as a key factor and the emergence of Industry 4.0 opens up an array of advantages, resulting in the improvement of communication along the value chain and enhancing the customer's experience. The high level of integration and the autonomous exchange of information will allow real-time change of requirements. Additionally, smart products will provide relevant information to their users about their status and utilization parameters. Briefly, smart factories are connected to a value chain in order to fulfil market requirements and consist of the integration between machines and materials through standardized interfaces. Smart materials and smart products are tracked along their whole lifecycle time, allowing a high degree of customization. Industry 4.0 is bringing the emergence of new business models that better meet customers' changing requirements, through the real-time communication capability along the whole supply chain.

1.1 Motivation

Focussing our area of study towards the area of production systems and manufacturing industries, we can notice that there has been a continuous rise in automatization and digital intervention into the physical processes to either ease human effort or to make an advancement towards higher quality products, reducing defects and ensuring higher chances of repeatability as and when required. This has slowly lead to a phase where many scientists tried to find whether it would be feasible to replicate the entire process of physical production system on a digital ground and thus enable to study any probable loopholes or faulty factor in the system which would hamper the smooth running of the system.

However, the challenges in building a digital production system are very high. It is not because of the fact of making the replica of the system is difficult and to make it function in real-time and in sync with the actual physical system is further difficult, but the fact that this digital system should be able to help in making the production system more robust and also being able to support in other activities of planning and control of the production system, to speak of a few important ones like being able to follow the lean production techniques like implementation of Kaizen, 5S, process stability with flexibility, JIT and parts/product flow, and most importantly of course keeping in mind the quality-cost-delivery factors and other factors of lean production system, depending on the complexity of the system. For this, there are 2 most important requirements: for one, the production system should be able to link/connect remotely to the physical production system, and secondly, it is essential that this digital system is able to perform like a self-learning playground, gaining information from the physical system and on a longer run able to correct itself for a better control on the physical system for the consecutive processes. This entire activity calls for the concept of two major applicative scenarios of the digital world, namely machine learning and the Internet of Things (IoT).

The traditional factory system will differ from Industry 4.0 in ways more than simple digitization or automation. Figure 1 demonstrates the same.

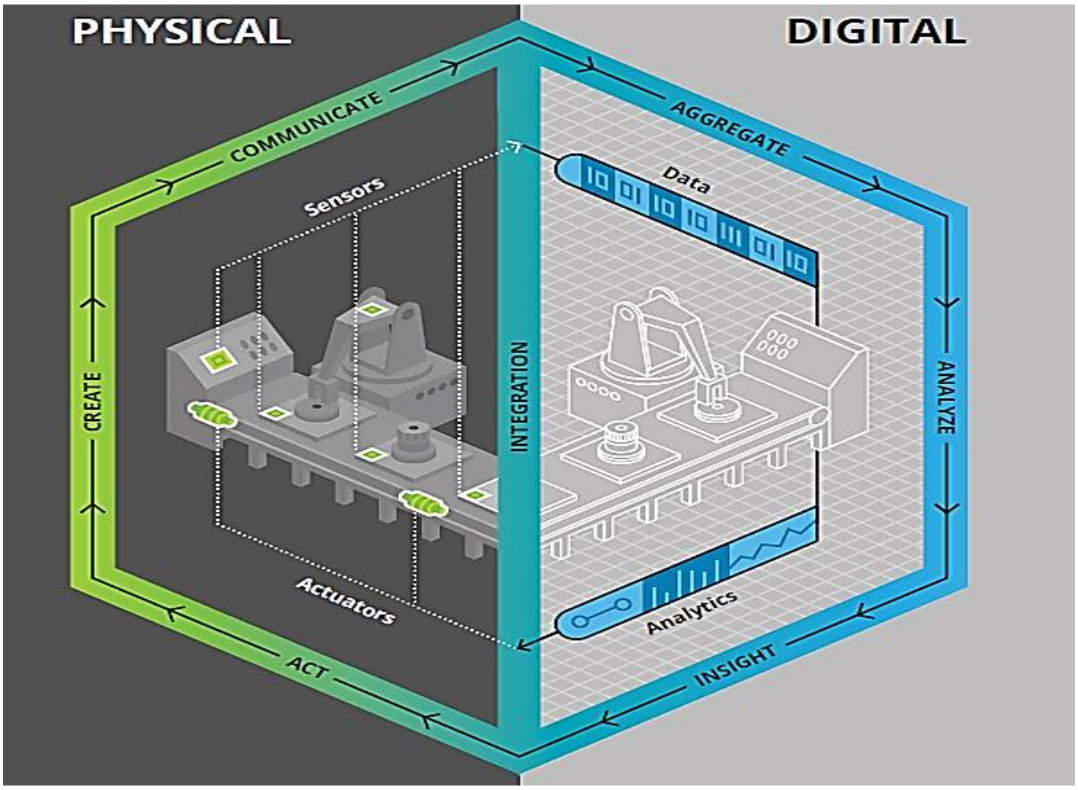
Figure 1 Comparison of today's factory and an Industry 4.0 factory

	Data source	Today's factory		Industry 4.0	
		Attributes	Technologies	Attributes	Technologies
Component	Sensor	Precision	Smart sensors and fault detection	Self-aware Self-predict	Degradation monitoring & remaining useful life prediction
Machine	Controller	Producibility & performance	Condition-based monitoring & diagnostics	Self-aware Self-predict Self-compare	Up time with predictive health monitoring
Production system	Networked system	Productivity & OEE	Lean operations: work and waste reduction	Self-configure Self-maintain Self-organize	Worry-free productivity

Source: Jay et al (2014)

Let's have a look at how this is possible to be explained by a representative schematics as in the figure below and how it might look in the future.

Figure 2 Manufacturing process digital twin model



Source: Deloitte University Press (2015)

This lead to a curious search for what are the options that could be explored for further research and/or application of the components of the next industrial revolution, as popularly described as Industry 4.0. After studying the scope and feasibility possibility, the area of Computational Vision(CV) was selected.

1.2 Related Work

The field of Computational Vision has been started to be explored since as long as the 1960s, but there has not been a major application done, due to various factors, the most important ones being the computational capability of computers, image quality due to progressively slow development of image sensors until the beginning of 21^{st} century and finally, the lack of digital applications in the production sector, apart from some level of automation achieved through very limited scope robots.

With the advancement in this century, the digital industry took a huge leap through the application of compact chips and thus computing capability, highly sophisticated and precise sensors of the image were being introduced in the market. Coding reached another level of proficiency, thus creating a series of advancement in robotic advancements. And all this started to take shape in the real world during the last two decades.

1.3 Research Problem

The research problem for this dissertation can be defined as to understand how the applications of Computational Vision can be applied in the assembly line of the Learning Factory or the Fabrica do Futuro (FF). The specific scope also shall extend towards the deeper understanding of how the various parameters of the light and ambience affect the application of Computational Vision. Finally, the major challenge for this study is the representation or actual physical setup of the application of the Computational Vision in the assembly line through an extensive hardware and software support of our partners MVISIA (Máquinas de Visão e Inteligência Artificial) and PPI-Multitask (Brazilian company in São Paulo specialising in operational excellence using MES, IoT and automation).

1.4 Objectives

In this dissertation, the main objectives would be to work in close collaboration with the setting up of the FF and the first phase of the implementation of Computational Vision in one of the workstations of a planned assembly line for the process of assembly of a smart skateboard, having also an application of the IoT components. This work has a scope limited to the focused study of Computational Vision only. However, the scope is also extended to the understanding of how computational vision forms an integral part of Industry 4.0 and how it might evolve in the future for deeper and further applications.

1.5 Research Methodology

In order to understand the importance of Computational Vision in the context of emerging Industry 4.0 as a complex technological system, and to understand the integration and application of the same for eventually establishing the CPS, a comprehensive literature review was carried out. The scientific literature databases, conference papers, journal articles, books, and other documentation, were utilized as the source of secondary data. To add upon that, a few online articles and blogs were also referred to for keeping an updated and well-informed summary of the Furthermore, the literature review was conducted considering the following electronic databases: ISI Web of Knowledge, Elsevier (Science Direct), IEEE Xplore digital library and other publications found available from the internet.

To have a better relevance on the fluidity of this dissertation, a simple generic method of snow-ball technique was adopted to do the literature review for insights on the vast realm of I4.0 and Computational Vision.

The step by step progress of the research work and the implementation of Computational Vision at FF has been subdivided in the following sequential order:

a. Identification of the current state of I4.0 in the practical arena.

b. Identification of the work done in the area of I4.0 in co-relation to the involvement of integrating the factor of Lean manufacturing methods.

c. The extent of evolution of digital models to be capable of handling Big Data and the Internet of Things.

d. The integration challenges faced previously to smoothly synchronize the digital and the physical world, that is the CPPS architecture.

e. The regional analysis of the variation in the development of the I4.0 concept in terms of machine learning.

f. Understanding in depth how Computational Vision has evolved over time and what are the main applications in different areas, be it commercial, production, health, security and henceforth.

g. To understand the scope of Computational Vision in the FF for the assembly of a smart skateboard.

h. Once identified, to develop the schematics of the activities in order to have an operating system of Computational Vision in the specified sector/workstation of the assembly line.

i. MVISIA in collaboration with PPI-Multitask to support in the establishment of the hardware, the background programming, machine learning process through data accumulation.

j. Thereafter, the interface which is to be made available in the decided workstation.

k. After the setup has been done, it goes for the trial runs. The required modifications and adjustments in the program are to be standardized.

l. The demonstration of the application of Computational Vision has to be done for the public, ranging from students, industry personnel and interested individuals taking up research work about Industry 4.0 and in the related fields.

2 THEORETICAL BACKGROUND

On having decided to focus on the area of Computational Vision of the I4.0, it was important to have a look on the studies conducted previously related to the I4.0 and how the major principles used in manufacturing until today since the beginning of the previous industrial revolution and how the evolution has occurred giving rise to the increasing focus on the implementation of this technique in the scenario of various industrial processes.

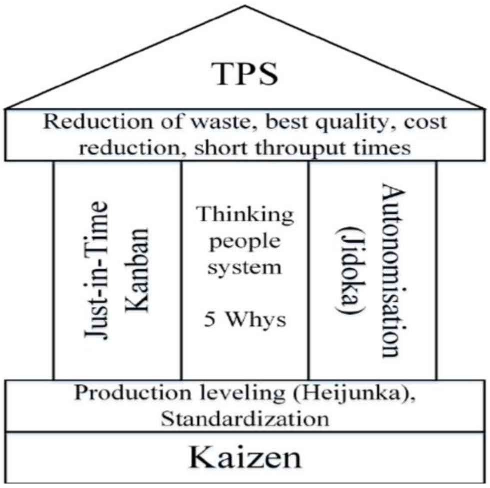
2.1 Lean Manufacturing System

Almost synonymous to the terminology of Toyota Production System (TPS), since inception till date there has been a great evolution in which the Lean concepts of manufacturing has been implemented, however, the foundation principles of Lean has remained the same since ever, and it is to totally eliminate the seven forms of waste known as Muda and reduce cost of production through continuous improvement called as Kaizen (MONDEN,2012). This well explains why the importance of Lean is undeniable and has to remain an integral part during the creation of the digital model that is created for any given specific physical system. The main functional areas of TPS summed by Wagner et al. (2017) are as below:

- ✓ 5S;
- ✓ Kaizen;
- ✓ Just In Time (JIT);
- ✓ Jidoka;
- ✓ Heijunka;
- ✓ Standardisation;
- ✓ Takt-Time;
- ✓ Pull Flow;
- ✓ Man Machine separation;
- ✓ Waste reduction;
- ✓ People and Teamwork.

The main principles or elements around which a lean manufacturing system is developed was best explained with inter-related functions in a broad manner by the following model of House of TPS (FRITZE,2016).

Figure 3 House of TPS



Source: Fritze (2016)

To analyze the actual connect of Lean Manufacturing principles and Industry 4.0, we must, we must look at one of the work done by Tobias Wagner et al, by doing a matrix mapping of the key elements of lean manufacturing systems to the ICT driven Industry 4.0. The study was done based on the rating provided as follows:

a) For a low positive impact on the Lean principles, "+" is used

b) For a high positive impact, "++" is used

c) For the highest positive impact of technology, "+++" is used.

Table 1 Mapping the role of ICT elements to Lean Manufacturing KPIs

	Data Acquisition and Data Processing				Machine to Machine Communication (M2M)		Human-Machine Interaction (HMI)	
	Sensors and Actuators	Cloud Computing	Big Data	Analytics	Vertical integration	Horizontal integration	Virtual Reality	Augmented Reality
5S	+	+	+	+	+	+	++	+++
Kaizen	+	++	+++	+++	+++	+++	+++	+++
Just-in-Time	++	++	+++	+++	+++	++	+	++
Jidoka	+	+++	+++	+++	++	++	+	+
Heijunka	++	++	+++	+++	+++	++	++	+
Standardisation	++	+++	+++	+++	++	++	+++	+++
Takt time	+	+	+++	+++	+++	+++	+	+
Pull flow	++	+	+	+	+++	+++	+	+
Man-machine separation	+	+	+	+	+	+	+++	+++
People and teamwork	+	+	+	+	+	+	+++	+++
Waste reduction	+	+	++	+++	+++	+++	+	+

Source: Wagner et al. (2017)

When we look at the above mapped tabular image showing the impact of Industry 4.0 in terms of the key indicators of the Lean manufacturing systems, we come across a few startling facts which gives us a better picture of the direction of Industry 4.0 and how it is essential to preserve the identities of lean manufacturing even going into the future of I4.0. Focussing on the column of ‘Virtual Reality’, we can note that there is a high impact of these characteristics in a major way for the improvement in quality and standardization of the production system, thus having a high impact in the Overall Equipment Effectiveness(OEE). Meanwhile, it enhances the removal of dependency of the machine to the operator, thus easing in the work productivity of the machine as well as the operator, who can, in turn, focus on a more complex set of tasks requiring higher human intervention.

Lean Manufacturing methods have long been deeply interwoven in the production systems of the current generation because of the benefits associated along with the implementation of the ingredients of the lean methodologies.

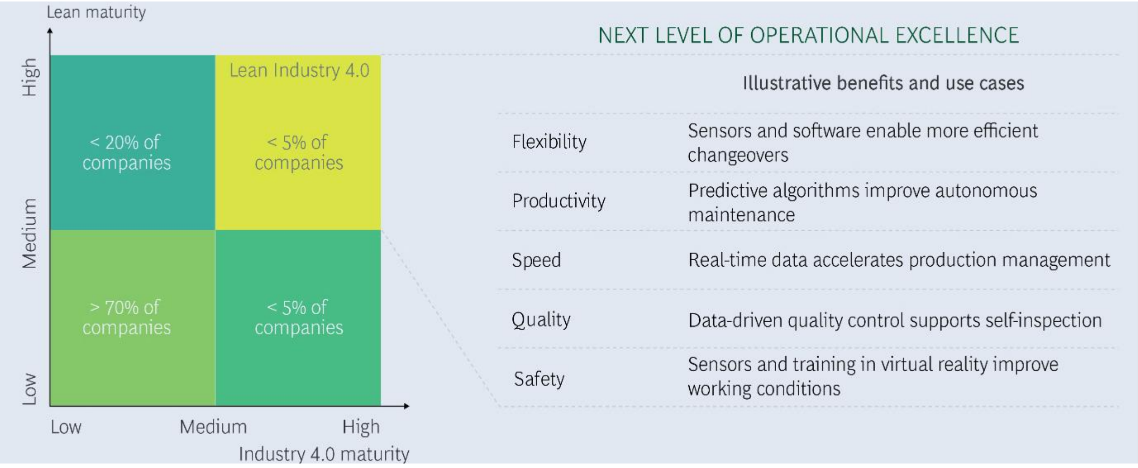
As per the Toyota Production System, in a particular work, Womack and Jones (1996) derives 5 main principles of lean thinking, namely, value, value stream, flow, pull and perfection. Together with those 5 principles, in the research work from Bauer et al. (2018), has derived a co-relation with I4.0 and lean, which is described as below:

a) Value: Through I4.0, the value of a customer is enhanced by giving higher importance to the lead-times and 100% quality through the product traceability from manufacturing to delivery process.
b) Process Perfection: By applying Kaizen and Pull-system of the lean principles, process optimization would become the core of the operations of the I4.0.
c) Lean and Technology Complement: All the methods of the Value Stream mapping of the Lean principles are further strengthened by the application of CPS through the I4.0 framework.
d) Improvement with Skilled Personnel: As described above, the replacement of manual tasks by robots is essential but under the controlled supervision skilled personnel and required intervention for critical decision making situations.
e) Lean as the basis for successful Manufacturing: I4.0 technologies are at the core of implementing and optimizing the manufacturing process in the lean principles way.

Thus without much conflict, it can be said that the implementation of I4.0 is like a symbiotic effect for the cause of uplifting lean principles. There was a question on how the impact of I4.0 will have on the business aspects of any industry.

One of the interesting analysis put forward in an article by Daniel et al.(2017), in one the article from Boston Consultancy Group (BCG, 2017), to highlight the advantages that are being brought in together by the Lean manufacturing principles and Industry 4.0 from the perspective of business and operational management, is shown below:

Figure 4 Industry 4.0: Rise of Operational Excellence and Revenue



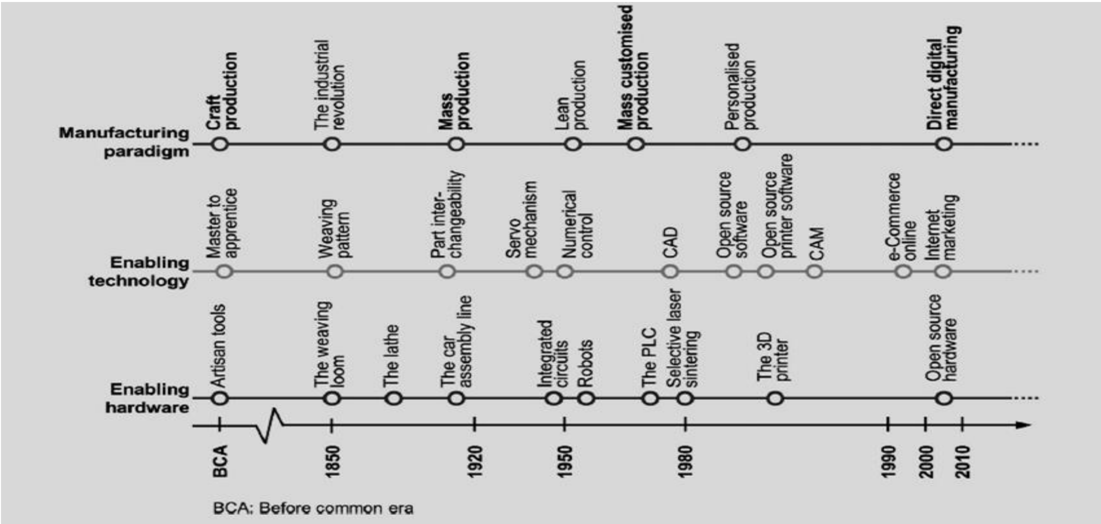
Source: BCG Experience on Industry 4.0 (2017)

2.2 Automation In Manufacturing

Any machine-controlled operation for the purpose of assembly or manufacture purpose and that carries out itself is termed as automation. This is aimed at reducing human efforts and also increases in efficiency of the overall process. The history of automation dates back to the period of implementation of the production line in the Ford Motor Company assembly plant in 1913. Next came the advanced timers and relays being used by the Japanese manufacturing industry, followed by the use of pneumatic and hydraulic actuators. However, the actual implementation happened with the introduction of electric components, circuit board and controller logic boards, computers and finally the robots, being controlled by all the above and to add upon it, sometimes even by the use of feedback control loops.

And slowly it has evolved to the current stage where the control of manufacturing is not just controlled by logic and programming but is being in certain cases able to re-adjust and self-modify to the needs and demands of processes involved. Below is a representation of the timeline evolution of the technologies.

Figure 5 Timeline for Evolution of Technologies



Source: Chen et al. (2015)

2.3 Virtualization

Talking about virtual aids in the domain of manufacturing, it is not new. The first introduction happened with the use of Computer Aided Processes (CAx), in different phases of manufacturing, starting from factory plan layout, to installations and process control in multiple phases through the use of computers. Then came the era of Computer Integrated Manufacturing (CIM), where the use of digital technology went up a few notches further. However, in the current generation, the use of computation has reached greater heights and forms the main part of this framework of the entire production system which starts at order reception at the customer end until the final stages of life-cycle management of the product. An immersive involvement of multiple factors within the domains of Total Quality Management (TQM) and Lean Manufacturing, translates into a larger spectrum termed as the Direct Digital Manufacturing (DDM). With the intensive research activities in vogue currently in the area of Cloud-Based Digital Manufacturing (CBDM), calls in for an array of support entities like CPPS, IoT and Big Data.

So how does a virtual factory look like? There is no clear imagery or a defined layout/architecture, but below is a probable vision for the architecture of a virtual or smart factory (PARITALA, 2017).

Figure 6 Architecture of Virtual Factory

Source: Paritala et al. (2017)

For a successful implementation of a virtual factory, after studying the successful implementation in various countries, Kang et al. (2016) also suggested that a simultaneous and balanced level of a bottom-up and a top-down approach is very essential, from activity management as well as technical implementation perspective. This balance is between what technologies already exits and the ones that are in their developmental stages.

In our case, in the implementation of Fabrica do Futuro (FF), we have adopted a very similar approach, however with a reduced level of application of automation hardware like robots and self-operating/self-actuated conveyers in the initial stages. However, with stages, the plan is to establish the FF into one of the state-of-the-art examples in Brazil for the demonstration of a Learning Factory for I4.0.

2.4 Use of Digital Technology in Manufacturing Control

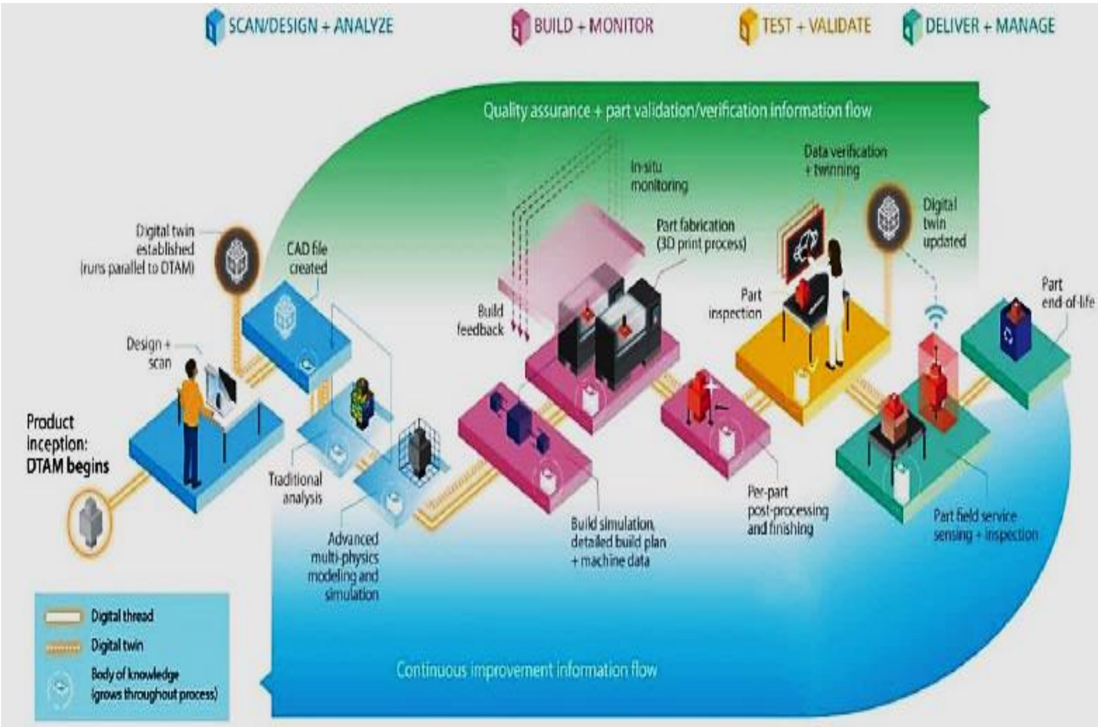
The evolution has seen a very high peak in the past two decades where the advance of the computer programming had a very rapid pace and with it, the applications of new logic and programming started to get implemented in the industry and production sectors. It all started with the use of Additive Manufacturing Processes (AMP), helped in the creation of digital and hence rapid prototypes which could be a good reference for design check before mass production. This also provided the ease in flexibility and customization scope.

Additive manufacturing, also known as layered manufacturing (3D printing, direct digital manufacturing) replaces process-based job shop operations. It introduces physical model driven operations based on a 3D CAD model (HOLMSTRÖM et al., 2016).

The 3D geometry is converted into a series of motion commands for an additive manufacturing machine by a class of geometric algorithms known as slicers. Digital thread for additive manufacturing (DTAM) is a single strand of data (COTTELEER et al., 2016) that originates from a CAD model in the design environment and moves towards a pre-processing environment in order to produce the required tool paths making up each layer. This is then followed by a manufacturing environment to fabricate complex shapes (STEUBEN et al., 2016).

Good alignment with AMP for the complete lifecycle data management is required to manage complex relationships between the part geometry, material and individual processes used to create the final part, termed as a whole to be AM-Informatics(MIES et al., 2016).

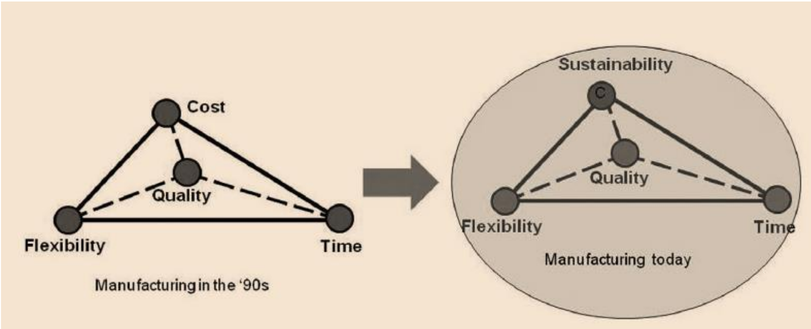
Figure 7 Digital Thread for AMP



Source: Cotteleer et al. (2016)

Slowly as the rise in AM took up pace, there was an increased collaboration with the multiple other digital prototyping programs which are further reducing the use of physical prototyping, to an extent of the transition into the practice of reduction in physical testing, while trying to simulate and resolve the entire conception, design and development phase with the help of digital prototypes. Not very long back, this has been started to be called the Direct Digital Manufacturing (DDM). As the name suggests, it is not completely a dive into the Information Technology (ICT) based production, however it forms a main link between the additive manufacturing phase to that of the ICT based systems.

Figure 8 Manufacturing Decision Making Attributes



Source: Salonitis et al. (2013)

Another important aspect worth noting here is that in the final phases of the 20th century and the entire of the 21st century the subject of sustainability has been a topic of major concern and consideration, because of the steep rise in the growth of the technology for the digital manufacturing. Thus a few of the key performance indicators were created which could highlight and score the various phases of the life-cycle of the product under consideration. Since sustainability forms a major aspect of the DDM, it is important to understand how the various major parameters of the sustainability dimensions are affected. Thus the major implications were cited below in Table 2.

Table 2 Major Implications of DDM on Sustainability

Economic	Environmental	Social
▪ Higher material utilisation (+)		▪ equal possibilities to all participants in markets and societies (+)
▪ Simpler, more efficient supply chains with less transportation efforts (+)		▪ bridge technological, educational and cultural gaps between developing and developed countries (+)
▪ Less material and energy losses due to less inventory (+)		▪ user oriented products, more customer satisfaction (+)
▪ Less waste and better waste management through possibility of direct recycling (+)		▪ potential benefits on human/worker health (+)
▪ User oriented manufacturing, less over-production in stocks (+)		▪ unclear impact on an employment situation of industry (+/−)
▪ No moulds etc. necessary (+)		
▪ Higher specific energy demand (−)		
▪ Quality issues are not finally solved, thus risk of bad parts and rework (−)		
▪ Potentially higher profit due to customer specific solutions (+)	▪ Ambivalent studies in terms of an environmental impact or eco-efficiency, (+/−)	
▪ Profitability could be proved in selected cases (+/−)		
▪ Longer manufacturing time (−)		

Source: Chen et al. (2015)

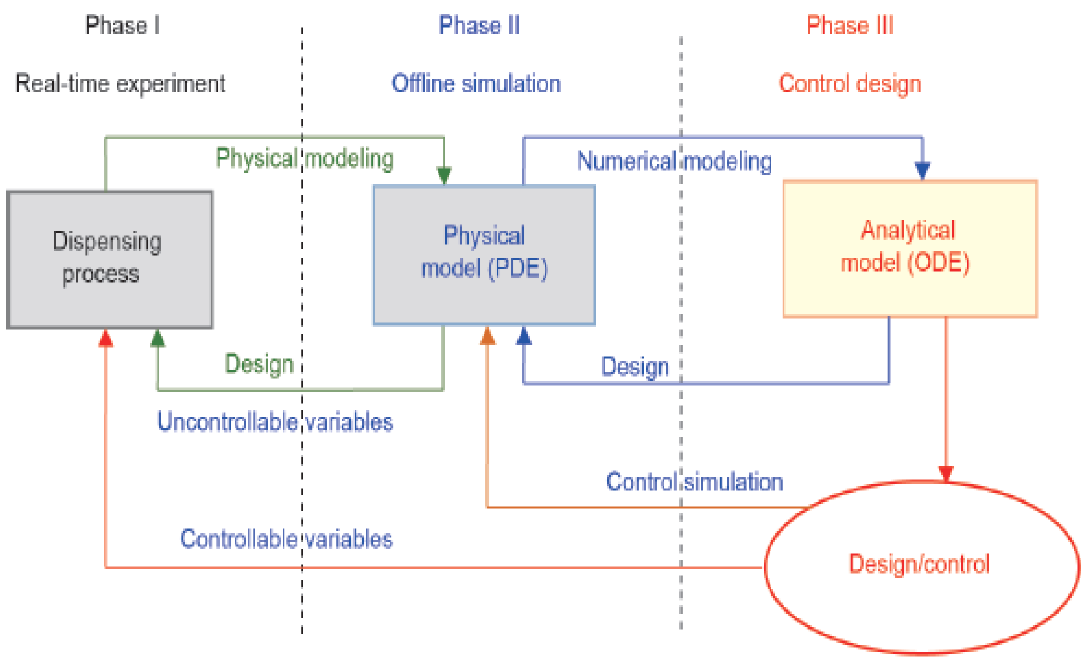
Apart from the sustainability factors, a major list of challenges has been highlighted by the work Li and Si (2017), wherein they speak extensively on the major challenges in the real-life scenario when we are talking about digitalization and control of manufacturing. Some of the interesting points that are highlighted are the complexity in the handling of processes are the likes of multi-time-scale processes, space-time dynamic processes and multi-level hybrid processes.

Well, it's not just the processes that have complexities, but also the control system and their variations, like logic-control, loop-control, supervisory-control, scheduling of operation at shop-floor level.

Also, the challenges of business-activity management at the factory level could prove to be a challenge, especially when there is a combination of one or more of these parameters involved in conjunction within a single production site. Thus they suggested a bottom-up approach wherein the gradual build of the system is done from dynamic modelling to control to supervision, finally also considering plant-wide activity management.

The following schematic is what they had suggested for the generation of model-based integrated design for manufacturing control:

Figure 9 Methodology for Integrated Design and Control



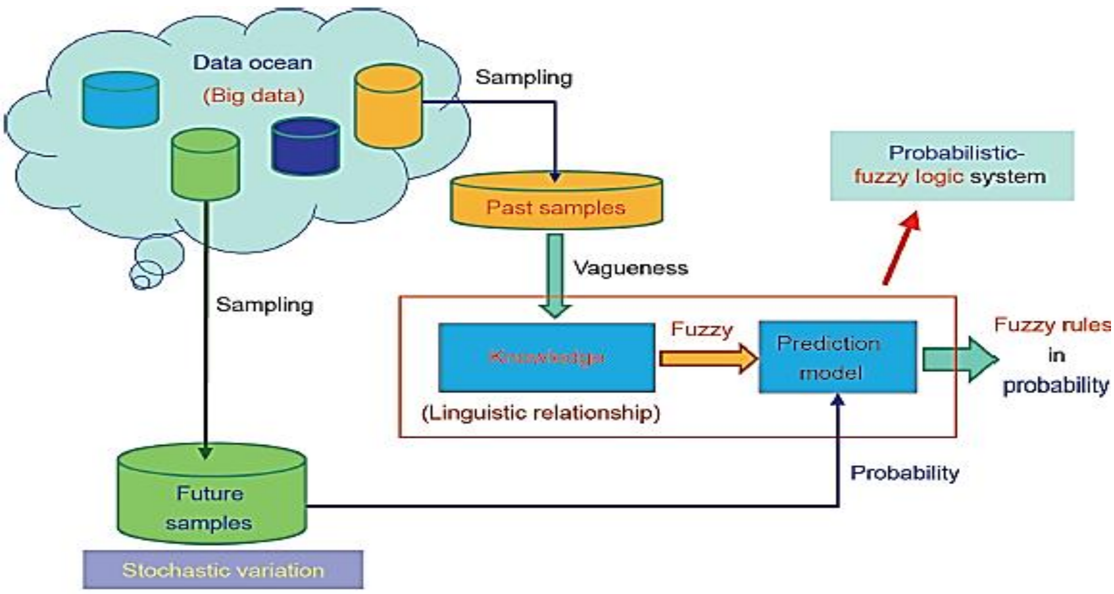
Source: Li et al. (2017)

As we observe from the Figure 9, the phase I involves the creation of a multi-sensing experimental platform to generate data for analysis, phase II is to physically test the analysis through an offline simulation mode and phase III is ultimate online prediction and design control phase.

In the functioning of these three phases, there is a very high probability of the phases having a conflict of application, feasibility, and timeline. Thus, they have all been connected through a cyclic loop, making them inter-dependent and in some ways, always progressing in sync, through continuous feedback loops.

In the case of the requirement of a high-level control, human decision-making skill is essential, thus a qualitative system based logic called fuzzy logic is very useful. It is a very good tool for knowledge extraction, however as many improvements have to be done with this system, one of the major being parameter calibrations in order to have better control in the arena of a complex system configuration.

Figure 10 Probabilistic Fuzzy Model



Source: Li et al. (2017)

2.5 Big Data Usage in Manufacturing Control

An extensive study from Babiceanu and Seker (2016) portrays a significant insight into the world of virtual manufacturing and the implications of the usage of Big Data in the same. They very well demonstrate the current and future outlook in the area of Manufacturing Cyber-

Physical System (M-CPS), where the vision of handling the production of the actual part will be handled by the M-CPS, whereas, the control and monitoring of these physical systems will be done by the advanced data processing and simulation modelling of the manufacturing and operational processes.

Thus Data analytics seem to be an inevitable ingredient to help the manufacturing world move into the zone of virtualization and cloud manufacturing paradigm. But here arises the concern of cyber-attacks and threats of hacks.

Though the process is a slow march towards the vision of cloud-based manufacturing, it goes without doubt that it is inevitable, hence the need to understand the multiple areas where loopholes currently exist and moving forward how they can be resolved with the support from the available IT tools. One of the major revelations in this direction was the introduction of ubiquitous computing to be implemented in ubiquitous manufacturing. Multiple authors have before suggested a wide array of implementation methodology at different levels of the production system, like communication between users through ubiquitous cloud computing, and from CAx to manufacturing assembly cells to decision support system. This leads to the management of a wide array of physical entities and also a series of virtual components which are meant to interact with each other on a dynamic basis with the support from an aspect of decision making, thus making the system even more complex and difficult to be modelled or simulated.

Another aspect of a smart manufacturing system is the involvement of IoT in the system. The major ingredients in the near future of the IoT involved manufacturing system are sensors, actuators, RFID tags and readers, GPS units, and high-definition cameras. These would form a bridge between the real and internet world of manufacturing and handle multiple tasks like sensing, calibrating, quality control, equipment monitoring, inventory monitoring and such. So the data generated from the ingredients of the IoT systems would be immense and has to be managed through an effective data handling system, hence comes the need of Big Data tools, like Hadoop, Yarn, and HiveQL. In general, the Big Data 3V's are Volume, Variety, and Velocity. Many other "V"s has been added like Value, Veracity, Vision, Volatility, Verification, Validation, Variability. Talking about Big Data projects implementation for manufacturing domain, Babiceanu and Seker (2016) goes on to say that it includes similar cycles as for the more general Big Data projects, like defining the business problem, research of data, cross-functional team formation, framing a roadmap for the project, data collection and examination, data modelling and analysis, data visualization, insight generation, integration with IT systems, and training professionals

The threat of cyber-attack is also an important area, where much care has to be adopted in certain specific areas like that of:

a) Data integrity attacks;

b) Replay attacks;

c) Denial of service attacks;

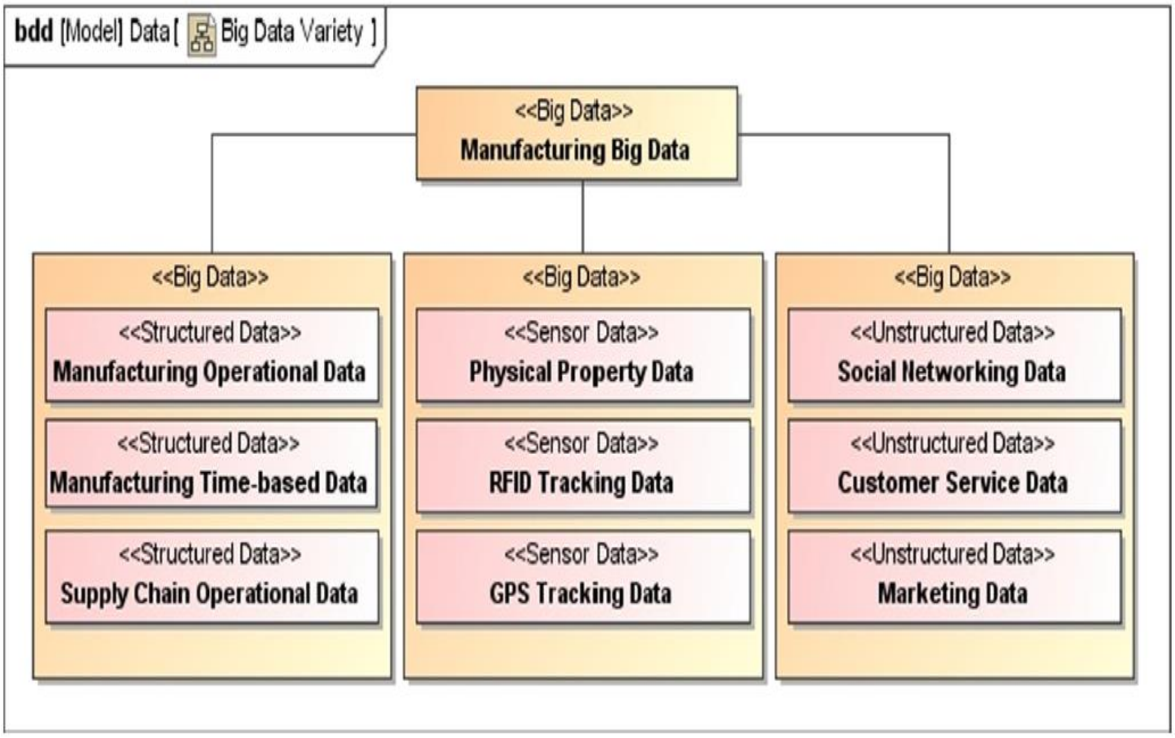
d) Timing attacks; and

e) De-synchronization attacks.

The suggested recovery from this kind of threat is suggested by the creation of a Dynamic Big Data Driven Application Systems (DBDDAS), a system which is very commonly used in disaster management and traffic management.

The consideration of the above discussions on Big Data leads to the formulation of the following chart:

Figure 11 Big Data in Manufacturing CPS



Source: Babiceanu et al. (2017)

2.6 Cyber-Physical Production System

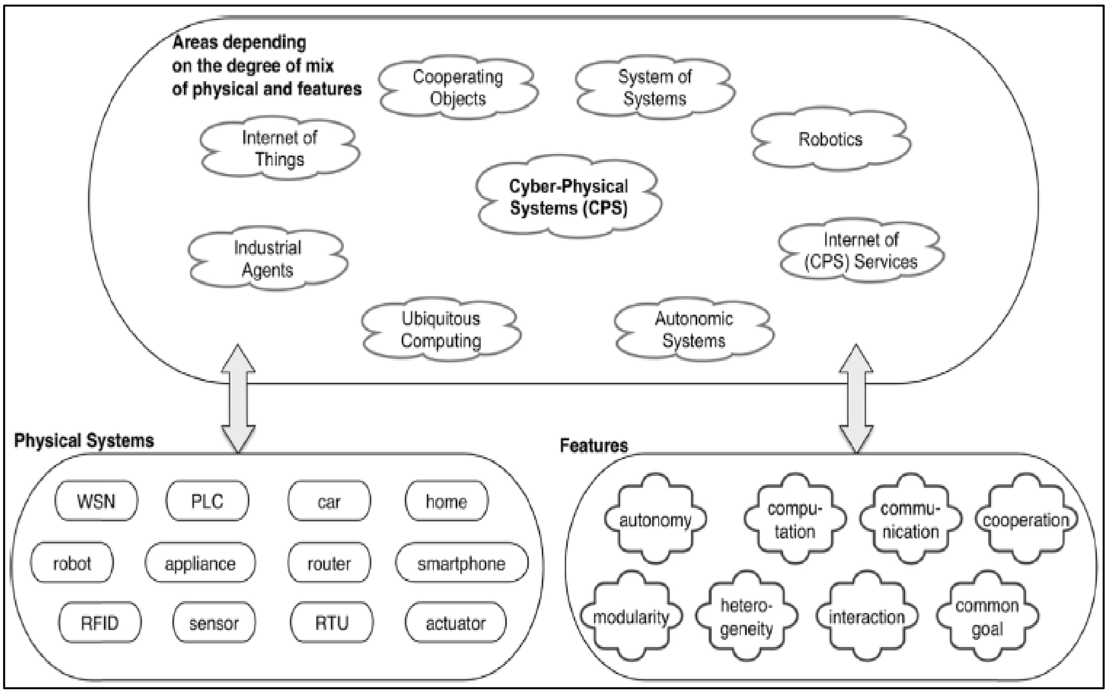
Cyber-Physical Systems(CPS) are defined as an ambient of leading-edge technologies which create and maintain a bridge between the physical and the computational intelligence world, with the goal of having more interconnected machines which are not just self-reliable and resilient, but also smart. The same, when applied specifically to the industry, is termed as Cyber-Physical Production System(CPPS) or Manufacturing Cyber-Physical System(M-CPS).

2.6.1 Cyber-Physical System(CPS)

The term Cyber-Physical System(CPS) emerged in 2006 amidst the work of a high-level working group in Austin, Texas (United States). This group of selected experts advocates mostly the co-existence of cyber and physical elements with a common goal and distinguishes between embedded system by putting the focus exclusively on integrating computational processes with physical processes. The need for the customization of products for multitudes requires a highly complex yet efficient form of a production system, which is not only flexible but also manageable or reconfigurable, keeping in mind the automation aspect.

Following is a figure explaining the zonal classification and responsibilities within a system and how a special zone created with a mix of the cyber and physical properties.

Figure 12 The Mix of Physical and Features for the basis of CPS



Source: Leitão et al. (2015)

CPS in industrial infrastructures also encompasses a coherent combination of electromechanical systems, mechatronics, systems of communication and information technology systems to operate and systematically control distributed physical processes and systems through rational logic that has been taught and fed in the initial stages and also which gets modified over the due course of time by self-learning process of machines from the ongoing activities on the shop-floor. Design of this is commonly found to be software and hardware devices which are webbed together along with systems, which have a higher level of decision-making capabilities This decision-making abilities are of two types in general, namely, autonomic, when it is able to coordinate self-decision processes, and, collaborative, when it makes negotiation-based decisions. These kind of decision-making capabilities are highly auto-upgrading through the usage of an array of supporting elements within this environment of CPS.

CPS can be considered as a smart system that uses cyber technologies embedded within and interacting with physical components, featuring a tightly knit coordination and a combination between computational and physical elements, integrating exchange of information, communication and control over a system through cyclic loops and based on learning and improvements codes.

In general terms, there are two approaches to look at the CPS: the Cyber-Physical Production System (CPPS) and the Manufacturing Cyber-Physical System(m-CPS). CPPS can be in simple words considered to be a communication system enabling machines to interact in an IoT environment, that is the connection between production technologies and the ICT. On the other hand, m-CPS can be considered as an advanced scope of the same CPPS where there is a communication between smart factories and the communication being enabled between many world-wide distribution production systems, thus creating a network of smart factories through the IoT enabled links

2.6.2 CPS Architecture

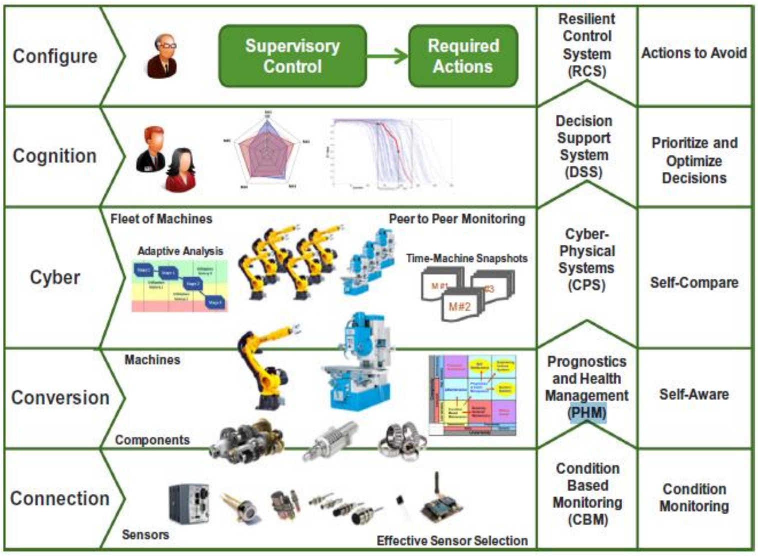
Based on the above discussions, we can have an understanding that the architecture meant for CPS is supposed to have 2 major elements:

a) Very sophisticated connectivity ensuring real-time data acquisition between the real world and feedback of data from the physical world.
b) Data analytics and smart data management within the cyberspace.

However, there are major challenges to get the above two actors working coherently. For tackling this challenge, Lee (2015) proposed architecture to layout the framework on which the smart factories could be built and based around. This architecture was called as CPS 5C Level and it has better clarity in explaining the sequential workflow from data acquisition to analytics and final value creation.

Let's look at the key parameters that were being considered to propose a sequential way to design the architecture for a CPS.

Figure 13 5C Architecture for CPS

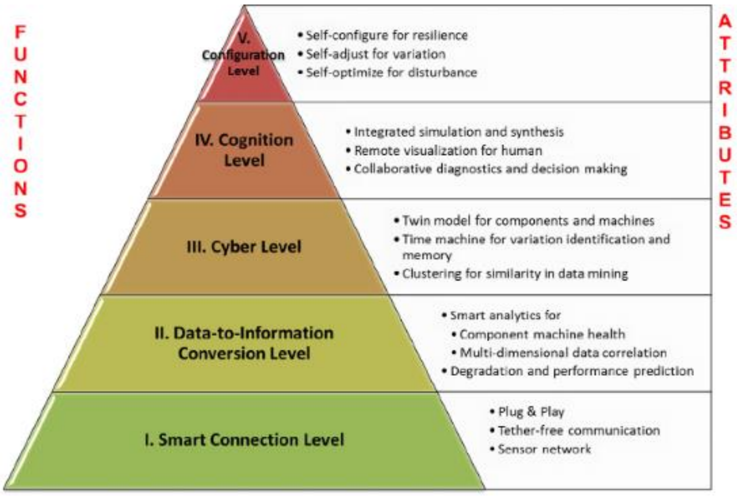


Source: Lee et al. (2015)

In this 5C architecture, it is observed that each of the 'C's in this model has equal importance, because, each of them is highly inter-connected and inter-dependent. Thus any weak link at any of these blocks shall turn out to be a reason of catastrophic failure in the process to establish an environment of CPS.

In the research by Lee et al. (2015), done to basically develop a CPS building guideline, was one of the visionary approach which actually forms the basis in which many following researchers have been taken up in the direction of framing the direction for creating a CPS and eventually a functional application of a prototype for the proof of a hypotheses. The implementation happens as shown in Figure 14.

Figure 14 Stagewise Implementation of 5C Architecture for CPS



Source: Lee et al. (2015)

In the phase of Smart Connection, a very good data collection is being ensured through multiple methods like sensors and controllers like Engineering Resource Planning (ERP), Manufacturing execution systems (MES), Supply Chain Management (SCM) and Coordinate Measuring Machinery (CMM). Here the major importance is to collect and tether data to central servers without a lag by the use of effective and essential sensors.

In the Conversion phase, the data collected should be able to convert into real-time actionable commands, such that decisions can be made accurately. This refers to the extraction and refining of the data in the form that could be able to be read through datum points and can be referred or taken as datum points for comparison, amongst many functions that this type of data must possess.

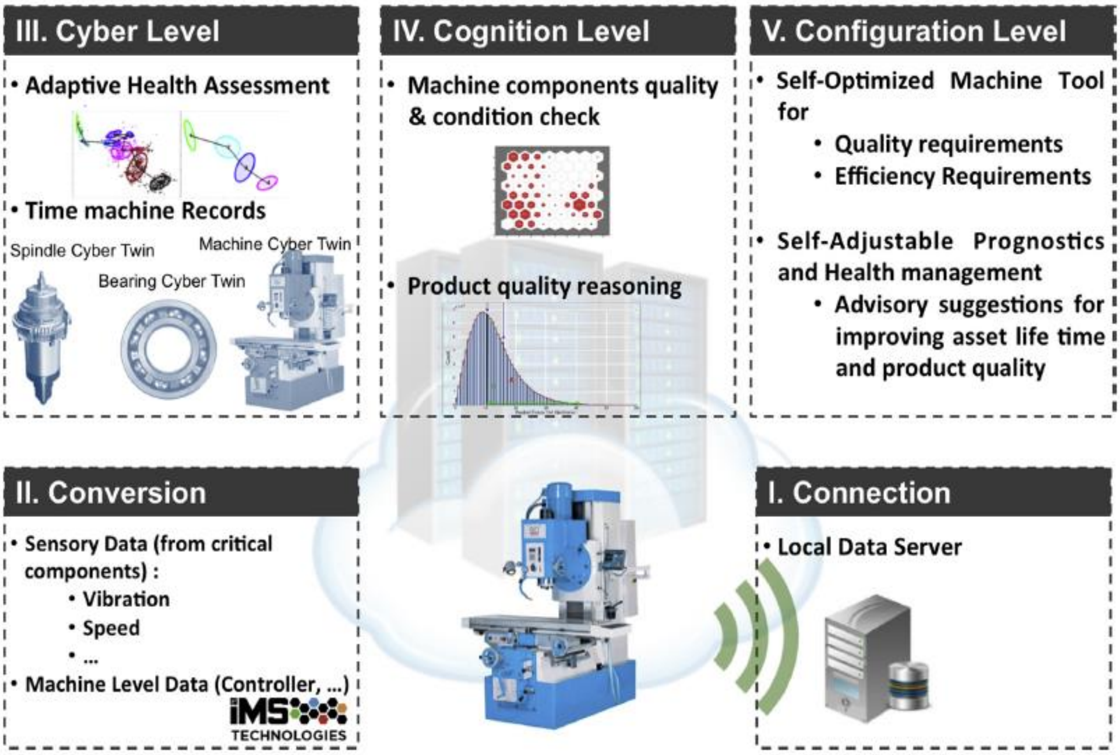
The Cyber level, as a matter of fact, acts as the central hub of information data from the participating machines in the environment under study and also there is a need to establish a system to segregate data between machines in order to make a correlation between actual functioning and required improvements. Cognition can be applied to the system through the knowledge of the data from the monitored system, in order to take correct decisions.

The phase of Configuration is actually the feedback control phase where a supervisory control is being taken by the cyberspace towards the physical manufacturing world for allowing the machines to become more intelligent, self-configuring and self-adapting.

In order to understand that why Prognostics and Health Management (PHM) is important, we must understand first that without its correct implementation, we cannot have a CPS, because in case the machines are physically not able to continue to operate, due to concerns over maintenance and over unpredicted stoppages, it will be ever more increasingly difficult for the systems to be in sync.

The concept of PHM for CPS system was suggested by Jay et al. It is found useful as there is a high possibility of a peer to peer exchange of data between intelligent machines, thus enabling the machines to self-efficient and self-reliable. This is generally achieved through the learning from the past of one or more machines and being applied for corrective actions, which were taken, based on the patterns. These processes thus not only maintain a link between the preceding and further stages but also keeps the cyclic loop of exchange of information intact, thus leading to a smoother CPS creation.

Figure 15 Information Flow based on 5C Architecture of CPS



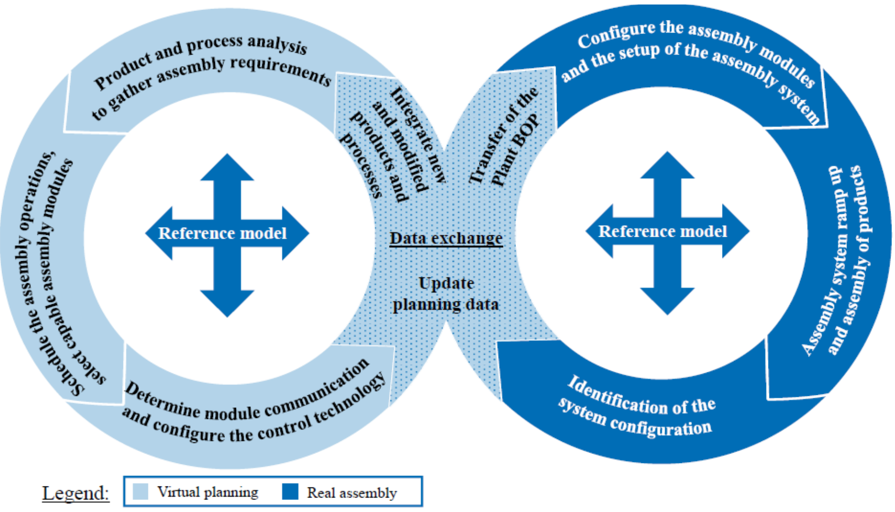
Source: Lee et al. (2015)

2.7 Feedback Loop in Between Virtual and Physical World

A very recent approach to the connection between the virtual and real world was shown by Müller et al (2016), in a recent work, as shown in Figure 16. What we can see is a proposed plan of information flow and exchange of data between the actual shop floor product and the control centre which is a virtual representation of exactly as the activities are on-going live on the shop-floor.

This forms an important part our study for the purpose of this dissertation because, our focus area, being the computational vision, is also a part of the continuous and large amount of information flow that happens between the physical component side and the monitoring side of the virtual component, which later frames the CPS.

Figure 16 **Approach to connect the virtual and real world of CPS System**

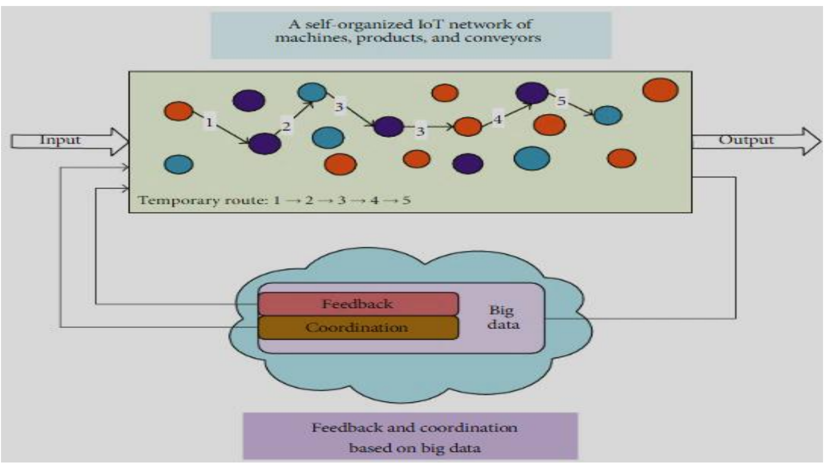


Source: Müller et al. (2015)

Another approach to the feedback based CPPS has been explained by Wang et al.(2016), where they describe smart factory's decision making and feedback control loop in the form of components of the CPS being classified in the form of various agents, which are interconnected and have a great flexibility in operation through the usage of concepts like autonomous decision making capability combined with the agility of distributed co-operation.

Let us have a look at this framework in Figure 17.

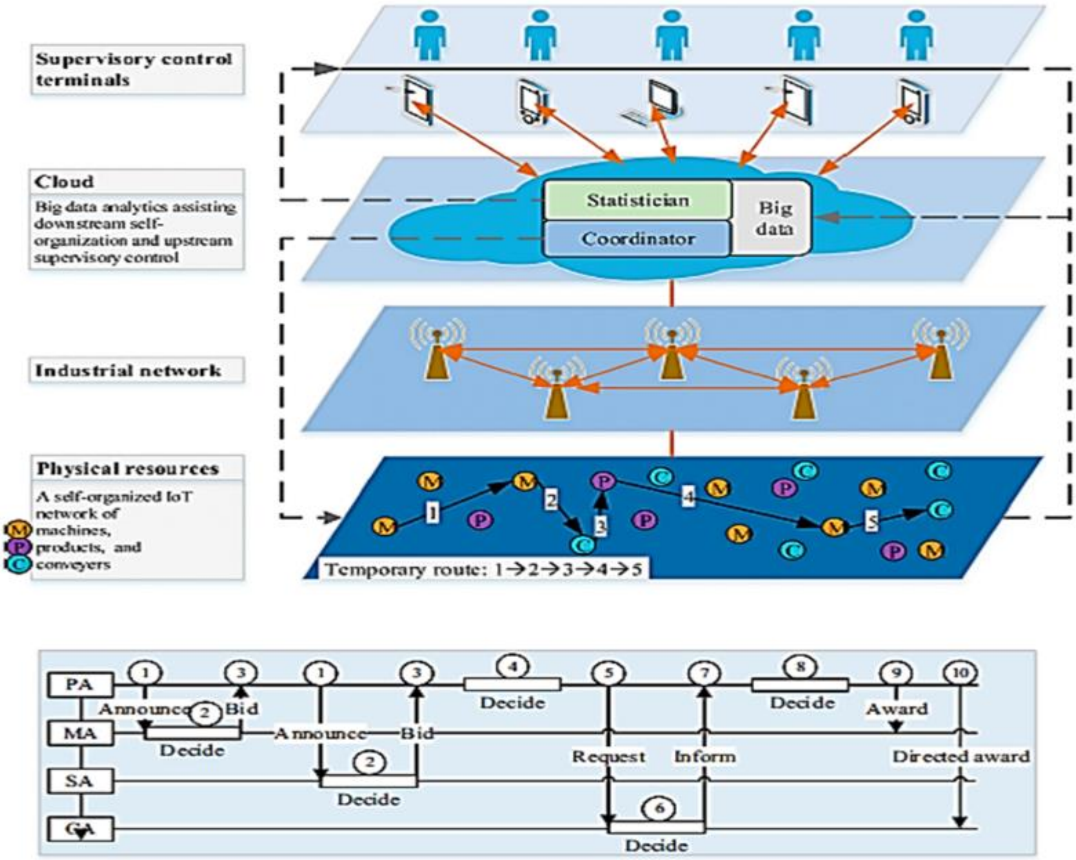
Figure 17 **Operational Mechanism of the Smart Factory of Industry 4.0**



Source: Wang et al. (2016)

As seen in Figure 18, it is actually an interaction and negotiation process that is happening between various classified agents termed as Product Agents(PA)representing the final products, Machining Agents(MA) representing the machines involved with the machining processes or testing and validation, Conveying Agents(CA) like the robots and the conveyor systems that mobilise the process line and Supplementary Agents(SA) representing the group of buffer elements that hold the PA.

Figure 18 Framework of A Smart Factory

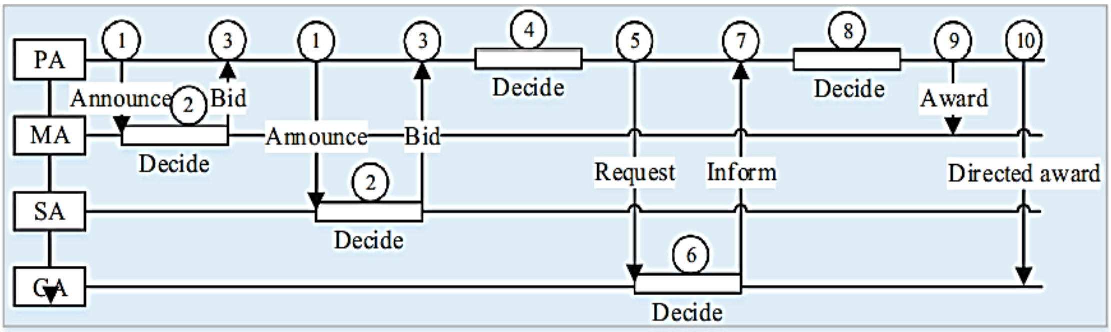


Source: Wang et al. (2016)

Now, when multiple of these agents come to make a decision and undertaking activity to deliver the requires result, that is a product, there has to be a co-operation strategy between them and a negotiation process has to happen, based on which a rational and logical decision is taken.

In the bottom part of Figure 18, the flow of information is showed for the decision process being taken by the movement of the information flows between various agents. The agents have been added as a legend for easier understanding.

Figure 19 Decision Making Amongst Agents



Source: Wang et al. (2016)

In Figure 19, the legends mean the following:

Table 3 Legends for Figure 19

Serial N°	Legend	Components Represented
1	Machining Agent (MA)	Machines that perform machining or testing operations.
2	Conveying Agent (CA)	Devices like conveyors, robots or AGVs that move the products.
3	Product Agent (PA)	These are the products that are processed by the system.
4	Supplementary Agent (SA)	Generally, the buffers that hold the PA agents.

Source: adapted from Wang et al. (2016)

In their work, they also give a very elaborate study on how these decision-making processes can be crumbled by deadlocks and what can be systematically done to overcome them.

2.8 CPS Benefits

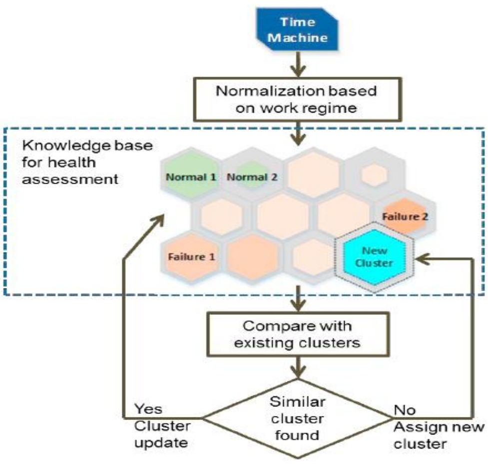
A distinct advantage that could be identified at this early stage of the research for the CPS implementation is related to machine learning. Machine learning is a method whereby algorithmic monitoring and selection of user preferences, a set of parameters are selected, based on which a preferential choice is being suggested automatically by the machine. It is not a new concept and has been implemented by multiple service industry organizations who strive to provide improved user experience, for example, websites like YouTube and Facebook, where user's navigation and preferential views are being used to provide further suggestions of content being specifically cured/selected by the machine.

Now, when it comes to the application of machine learning in the field of manufacturing industries, the scenario is a bit different. In here the selection is mostly done for the choice of parameters best suited for the production process, increasing efficiency like all the parameters involved in OEE(Overall Equipment Effectiveness) or in reducing wastes through lean production principles.

Let us take a look at one of the concepts suggested by Bagheri et al. (2015) in their paper where they made an attempt at giving a unified framework of CPS in the field of manufacturing and its allied activities. According to the above paper, although it is an early stage to identify the exact structure of the Industry 4.0, the applications of sensors, data acquisition system, cloud computing, and computer networks have propelled the establishment of an intelligent system which calls for a systematic approach to implement intelligent systems to the shop-floor. Thus, comes in the approach to have a system able to self-learn and self-determine the best processes, hence minimizing the waste and drop-time of production.

This could be bettered by a system termed as Adaptive Clustering Algorithm (ACA), derived from the famous algorithms like Self-Organizing Map (SOM) & Gaussian Mixture Model (GMM), however has the potential to self-cluster the best set of algorithms in a cluster based on a logic input directed by the user or system-controller at the beginning of the implementation. The process has been well demonstrated through the following schematic in Figure 20.

Figure 20 Adaptive Clustering Algorithm Schematics

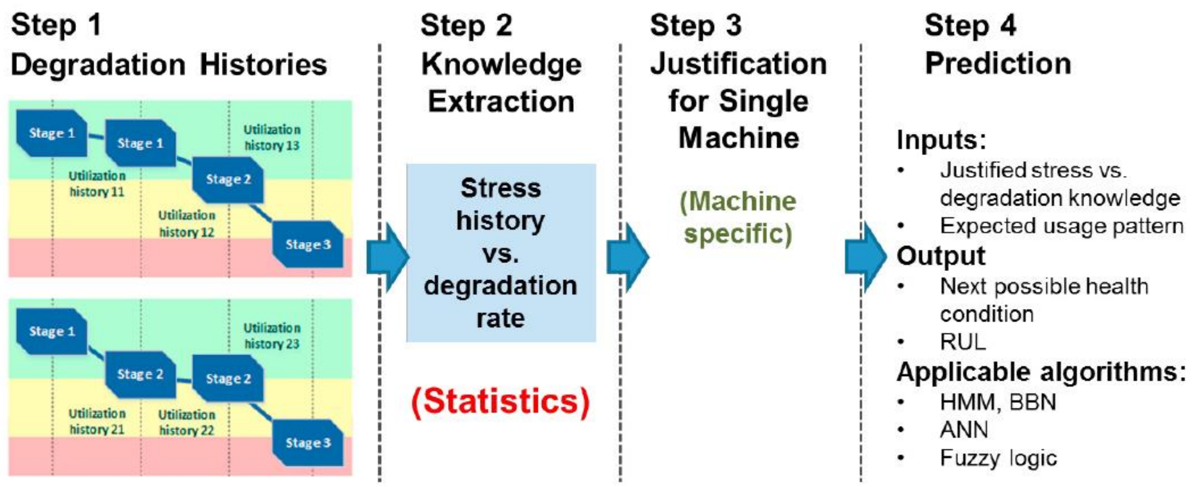


Source: Bagheri et al. (2015)

The above logic can then be utilized for the accumulation of performance of the actual manufacturing system and then be used for the health assessment for the future. The team also explained how the prognostics are to be done for the health assessment of the machines under complex and multi-regime conditions. In this aspect, there is an importance of identifying the remaining utilization life (RUL). Thus, a relationship is created between the utilization (stress) and machine degradation using measurement data from the data acquisition systems, emphasizing on the fact that the RUL is just not a factor of time, but multiple other factors ongoing in the shop-floor.

The step-by-step process of such an analysis is explained below:

Figure 21 Utilization of Matrix based Prognostics



Source: Bagheri et al. (2015)

The above process was being studied through a case study of implementing the same in a CPS enabled system and the comparison was drawn between the current traditional model of a factory and the Industry 4.0 production system. The comparison is displayed in Table 4, shows numerous benefits, as mentioned in the same work.

Table 4 Comparison of Traditional factory and the Industry 4.0 factory

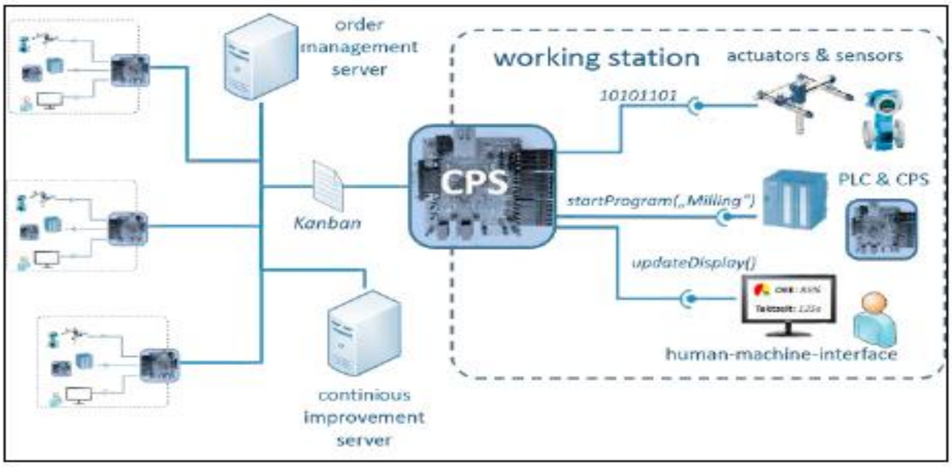
	Data Source	Today's Factory		Industry 4.0	
		Attributes	Technologies	Attributes	Technologies
Component	Sensor	Precision	Smart Sensors and Fault Detection	Self-Aware Self-Predict	Degradation Monitoring & Remaining Useful Life Prediction
Machine	Controller	Producibility & Performance	Condition-based Monitoring & Diagnostics	Self-Aware Self-Predict Self-Compare	Up Time with Predictive Health Monitoring
Production System	Networked System	Productivity & OEE	Lean Operations: Work and Waste Reduction	Self-Configure Self-Maintain Self-Organize	Worry-free Productivity

Source: Bagheri et al. (2015)

2.9 Model of Industry 4.0 in Terms of CPS and Lean Systems

A suggested model framework of the new format of the industry in concordance with Lean principles and utilizing the technologies (Key Enablers) was given by Kolberg and Zühlke (2015). CPS, as seen in Figure 22, works as an interacting medium between multiple systems in the framework, thus collaborating the data exchanges and hence the desired operations of the I4.0.

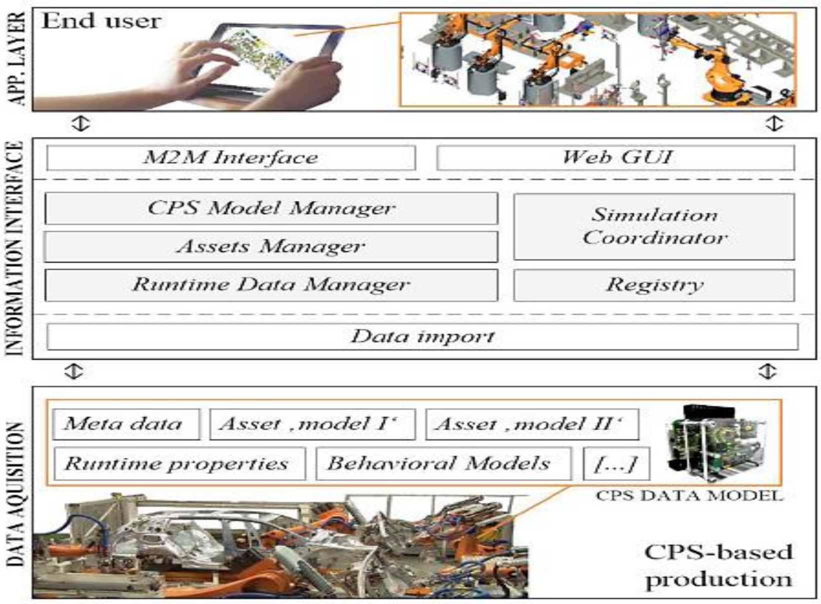
Figure 22 Example of CPS as Interface of WorkStations



Source: Kolberg et al. (2015)

Below is an excerpt of a three-tier model from Weyer et al. (2016) showing an example of the application of I4.0 in the automotive sector.

Figure 23 CPS & Multidisciplinary Seamless Interaction over Product Lifecycle



Source: Weyer et al. (2016)

2.10 Lean Manufacturing in Collaboration with Industry 4.0

According to the work from Mrugalska and Wyrwicka (2017), the 3 paradigms which are the defining components of I4.0 are:

a) Smart products, which are capable of taking the active role of requesting and providing production details like co-ordinates and dimensional values.

b) Smart machines, which are not hierarchical but decentralized systems that incorporating the part of CPS. Herein, the machines and products are able to self-communicate on different production parameters, thus making the production more adjustable and modular, rather than fixed.

c) Augmented operator, is the one who is more in control of the final decision making through mobile user-friendly interfaces and manually interfere in the process-control as and when required in the growing context of technical complexity.

And these three paradigms are used to create a link between multiple factors of the Lean system with the I4.0. Now the question arises, how do we do so? They explained it as follows: the smart product features allows for the data collection of a limited set of products thus allowing for the creation of a Current State Map, thus mapping wastes, strategic planning for future for Value Stream Mapping.

Coming to the Smart Machines, the Kanban panel application through data collected throughout the product creation in the previous stages or instances, helps in identifying the scope of improvement and the fail-safe poka-yoke can also be seamlessly implemented. Another major point is that using the concept of Plug-n-Play, the system could be flexibly configured in rapid succession.

The Jidoka quality control method hence comes into play, wherein the augmented operator can reduce the time between error occurrence and error identification through the CPS system enhancements.

However, in the work from Kolberg and Zühlke (2015), another aspect was described, termed as Smart Planner. This system would act as a means to integrate CPS, which could negotiate cycle times, hence optimizing the selection of capacity utilization per working station to that continuous flow of quality goods or zero-defect products. The below table shows a detailed co-relation:

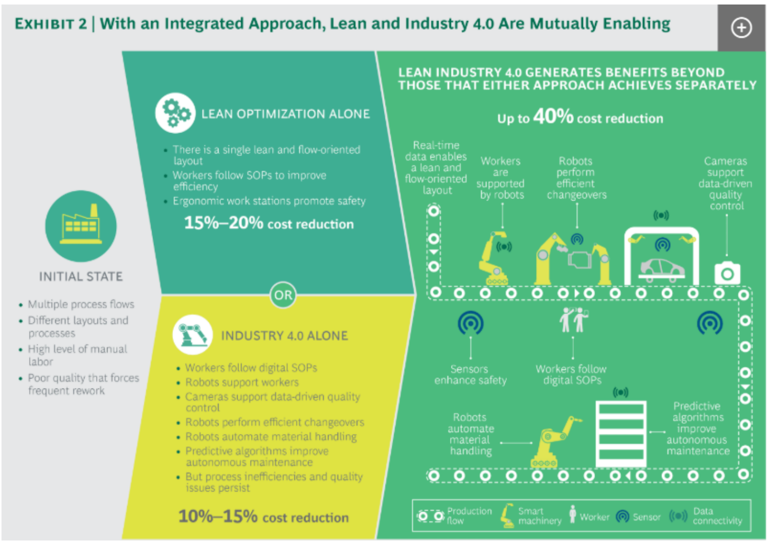
Table 5 Use Cases to Combine Industry 4.0 with Lean Production

Industry 4.0	Lean Production	
	Principle: Just-In-Time	Principle: Jidoka
	Method: Kanban system	Method: Andon
Smart Operator	Employee gets information about remaining cycle time via augmented reality	Wearable computing systems receive failures and display it in real time to the employee
Smart Product	Smart Product contains information of Kanban to realize an order-oriented production	-
Smart Machine	Machines offer a standardized interface for receiving and sending Kanban	Machines send failures directly to Smart Operators and call other systems for fault-repair actions
Smart Planner	IT systems reconfigure production lines and update Kanban according to the new configuration	-

Source: Kolberg et al. (2015)

A multitude of advantages has been observed in terms of economic benefits by the application of the combined view of Lean principles and I4.0 technologies. This study was done by one of the biggest players in terms of industrial consultants, BCG, 2017.

Figure 24 Combined Enablers: Benefits of Lean and Industry 4.0

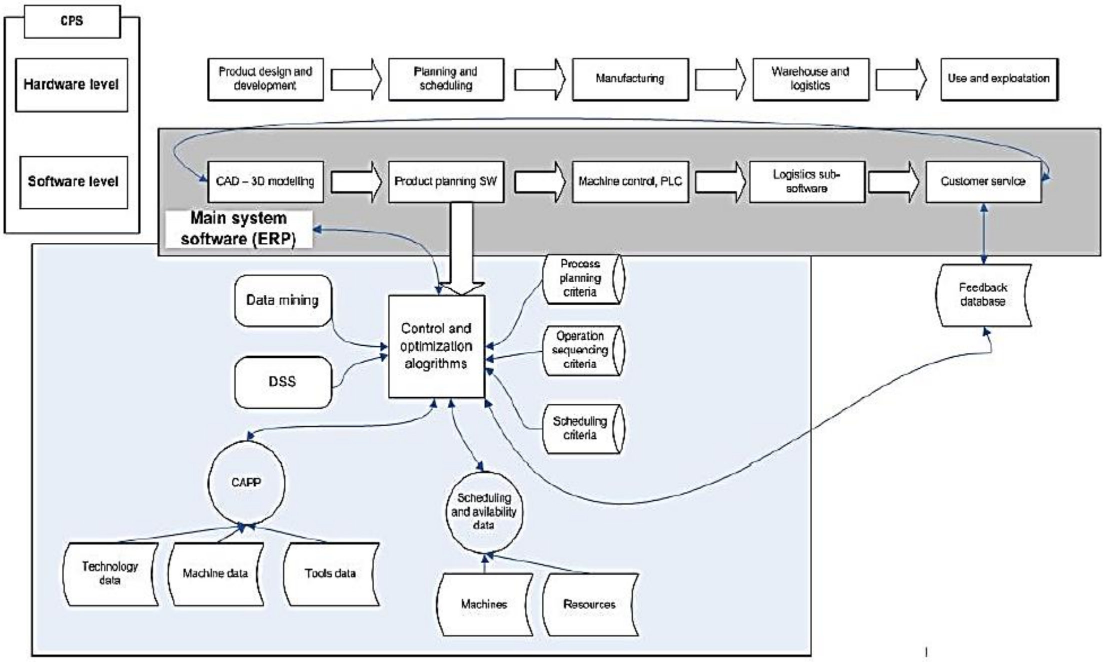


Source: BCG Analysis (2017)

2.10.1 Process Planner to Product Planner

Till now we have seen the structure of the I4.0, integrated with lean systems and having a framework of CPS. Now we shall take a look at the change in the approach for the I4.0 in terms of planning of operations given by TRSTENJAK and COSIC (2017).

Figure 25 Lean Systems and Cyber Systems of Industry 4.0 Planning

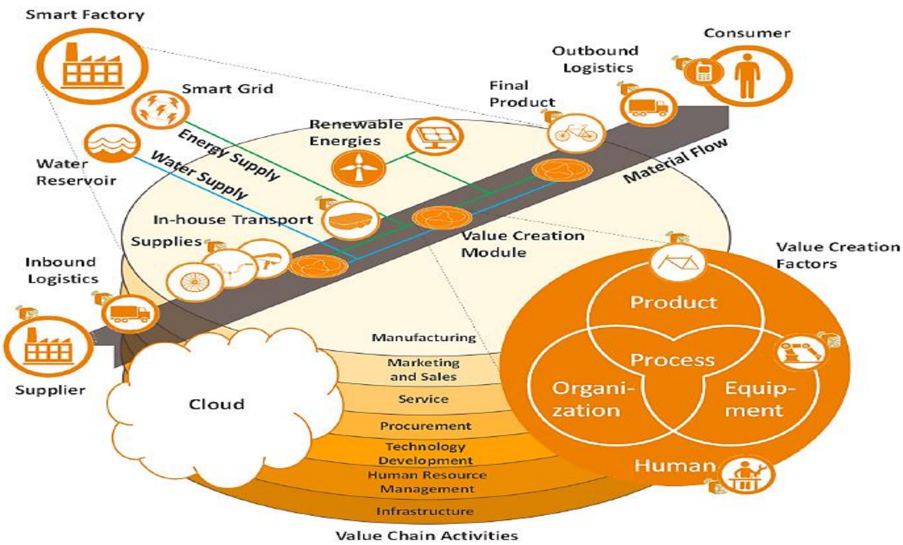


Source: Trstenjak et al. (2017)

2.10.2 Materials and Information Flow

In this paper, we do not deal in details on the material flow, however, we can have an overview of how the material flow occurs in the environment of I4.0

Figure 26 Lean Systems and Cyber Systems of Industry 4.0 Flow of Information



Source: Stock et al. (2016)

3 INDUSTRY 4.0: BRAZIL and EUROPE

Industry 4.0 or in short I4.0, is a strategic concept first generated by Germans, which involves the creation of factories which are intelligent and facilitated with upgraded systems like CPS, IoT and Cloud Computing. It opens up a whole array of research scope in each of the specific areas mentioned above and is still in a very early stage of progress. This new form of the industry will revolve around a plethora of technological advancements made by humankind in the wake of the 21st century, to name some of which are CPS, IoT, Robotics, Big Data, Cloud Manufacturing, Computational Vision and Augmented Reality. These will not only have a great impact on products but also change the scheme of processes that have been in practice since the last Industrial Revolution, often termed as Industry 3.0. This meanwhile will be effective in enabling efficiency and productivity improvements.

As mentioned above, the few key components of the I4.0 could be listed below:

a) Internet of Things(IoT): It is best described as the saying goes, “many-bodies-one-soul”. In actual, the concept is to create an inter-connected environment where multiple objects are linked together using sensors and other devices which could be used for data exchanges.

b) Cyber-Physical System(CPS): It is the mechanism by which the world of IoT is being realized to be practically viable. It involves a myriad of arenas deeply intertwined with each other, of the likes of mechanical and mechatronics, design and process sciences, informatics and cybernetics, to name a few. Embedded systems play a vital role in actualizing such a system in real-time.

c) loud Computing: It is a method of providing programmable services which are left for the options of scalability. It has led to a number of options open to the designers of the framework of the I4.0. The level at which real-time monitoring and simulation can be done using the DT model of the production system is being determined the criticality of the system.

d) Big Data Analytics(BDA): With the emergence and input of Internet and IoT leads to the emergence of huge volumes of data, referred to as Big Data, generally originating from sensors, devices, video/audio, networks, log files, transactional applications, social media feeds and the web feeds amongst others. The data at the current scenario is available in a streamlined fashion, however, the ability to use the data by screening the useful and garbage data, thereby making possible to take critical actions or decision for certain manufacturing processes as and when required makes it uniquely important for this function to be handled by an advanced analytics system.

e) Other Information and Communication Technology(ICT): It refers to the hardware and the software mechanisms which help in the storage, processing, and transmitting of the data that is being involved in the systematic operation of the I4.0 framework.

An elaborative study for the extent of application and implementation in 5 different areas, as mentioned above, varying across different countries around the world, was done in the work by Zhong et al. (2017), describing different aspects of IoT and cloud-based manufacturing and what applications are feasible, or already in development.

Table 6 Typical applications of IoT

Industries/companies	Aims	Improvements	Future research
Smart community, Canada and China	• Neighborhood watch • Pervasive healthcare	• Value-added services such as utility management and social networking • Suspicious event detection in neighborhood watch	• Cooperative authentication • Detecting unreliable nodes • Target tracking and intrusion detection
A cloud implementation using Aneka, Australia	• Sharing data between application developers • IoT application-specific framework	• A seamless independent IoT working architecture • Open and dynamic resource provisioning	• Integrated IoT and cloud computing • Big data for IoT applications
Healthcare and social applications, USA	• Improving the quality of human life • Examining potential societal impacts	• Enabling ambient intelligence • Ubiquitous communication • Increased processing capabilities	• IoT theory for management and operations • IoT data complexity analysis • IoT-enabled global business and commerce
Machine-to-machine measurement, Ireland and France	• Easing the interpretation of sensor data • Combining domains	• Cross-domain connection • Improved performance • Enhanced interpretation from users	• Domain knowledge extraction • Interoperable ontologies and datasets
Smart cities, Padova, Italy	• Providing open access to selected subsets • Building an urban IoT system	• Improved energy efficiency • Reduced traffic congestion • Smart lighting and parking	• Smart city data analysis • Smart connectivity • System extension
IoT Gateway system, China	• Helping telecom operators transmit data • Controlling functions for sensor network	• Improved functions such as data display, topology, etc. • Enhanced data transmission	• Advanced IoT Gateway functions • Security management
IoT application framework, India and France	• Developing an IoT application framework • Implementing the methodology to support stakeholders' actions	• Improved productivity of stakeholders • Improved collaborative work	• Mapping algorithm cognizant of heterogeneity • Developing concise notion for Srijan development language • Testing support for IoT application development
IoT-enabled energy management, Italy and Spain	• Illustrating energy management at production level • Proposing IoT-based energy management in production • Providing a framework to support the integration of energy data	• Integrated energy data management • Improved energy efficiency • Enhanced energy data analysis	• Conventional hypothesis testing • System extension
IoT-enabled real-time information capturing and integration framework, China	• Providing a new paradigm of IoT to manufacturing • Designing a real-time manufacturing information integration service	• Real-time information capturing • Improved logistics	• Optimal production using captured data • Prediction model of production exceptions

Source: Zhong et al. (2017)

Table 7 Typical applications of CPS

Industries/companies	Aims	Improvements	Future research
Power systems, USA and Canada	• CPS test bed implemented in RTDS and OPNET	• Providing a realistic cyber-physical testing environment in real time	• Studying CPS vulnerabilities in various power system models
Children keeper service, Korea	• Proposing a key design method for CPSs	• Designing CPSs with high-quality more feasibly and practically	• Data-driven CPS decision-making models
Water distribution networks, USA	• Integrated simulation method for reflecting the operation and interaction of CP networks	• Facilitating modeling CPSs	• Extending the models and techniques for other CPS domains
Civil structure, USA	• Developing and assessing CPSs for real-time hybrid structural testing	• Illustrating the feasibility of virtualizing CPS components	• Improving hydraulic actuator models • Quantifying further scalability of the proposed approach
Fire handling, China	• Developing a simulation model for emergency handling problems	• Obtaining optimal sensing and robot scheduling policies	• Increasing computational time for more complicated scenarios
Autonomous vehicles, USA and Germany	• Proposing a parallel programming model for CPSs	• Guaranteeing timeliness for complex real-time tasks	• Addressing the dynamic nature of CPSs in the proposed model
Intelligent manufacturing, Sweden and USA	• Associating a CPS with holons, agents, and function blocks • Using CPS to digitalize pneumatics with applications	• Ease of system implementation in decentralized or cloud environment • Maximized flexibility and advanced condition monitoring • Self-adjusting and self-adopting subsystem	• Practical in dynamic manufacturing with uncertainty • Time-sensitive networking for synchronized motion control • Distributed decision-making and self-organization between (sub)systems
Healthcare, Brazil	• Model-based architecture for validating medical CPSs	• Providing enough information to perform medical tests	• Proposing architecture for other medical device models
Communication, China	• Analyzing the features of machine-to-machine, wireless sensor networks, CPS, and the IoT • Reviewing home machine-to-machine networks	• Outlining the challenges related to CPS design	• Future design of CPSs

RTDS: real-time digital simulator; CP: cyber-physical.

Source: Zhong et al. (2017)

Table 8 Typical applications of Cloud Computing

Industries/organizations	Aims	Improvements	Future research
Business, France	• Proposing a method for cloud business applications	• Reducing the technical knowledge for provisioning cloud applications	• Integrating a discovery approach and semantic matching in the components discovery phase • Adding a negotiator module
National Natural Science Foundation, China	• Presenting a hybrid information fusion approach	• Achieving multilayer information fusion • Identifying global sensitivities of input factors under uncertainty	• More comprehensive information fusion approach
Business and healthcare, UK	• Developing cloud computing in the life sciences	• Introducing cloud models to life-science business	• Identifying major issues
IT and business, UK	• Highlighting aspects and uniqueness of cloud computing	• Examining the true benefits and costs of cloud computing	• Application extension in other industries
Manufacturing, Iran	• Proposing a service-oriented approach	• Adopting a layered platform (LAMMOD) for distributed manufacturing agents	• Upgrading the XMLAYMOD layers' procedures and structures
Education, India	• Outlining the benefits of using cloud computing for students	• Providing opportunities for students to test, learn, experiment, and innovate	• More cloud-based education applications
ICT, China	• Proposing a forensic method for efficient file extraction	• Efficient location of large files stored across data nodes	• Researching the parallel extraction method for a Hadoop distributed file system • Researching the analysis method on EditLogs
ISO-New England, USA	• Developing cloud-based power system simulation platform	• Security schemes • Cost savings	• Real-life applications of this system
Transportation, China	• Formulating a new entropy-cloud approach	• Solving the railway container station reselection problem	• Study, design, and plan for the transferring network

Source: Zhong et al. (2017)

Table 9 Typical applications of BDA

Industries/companies	Aims	Improvements	Future research
Google, USA	• Refining its core search and ad-serving algorithms	• Searching patterns and recommended searches based on what others have searched, external events, and etc.	• Studying the algorithm
Retailers, UK and USA	• Tesco: precise promotions and strategic segmentation of customers • Amazon: accurate recommendations for customers • Wal-Mart: supply-chain optimization	• Mining customer data from loyalty program • Recommendation engine based on collaborative filtering • Enabling vendor-managed inventory based on big data	• Reducing potential risks of sharing data • Avoiding using sensitive personal information • Protecting IT infrastructure from cyber attacks
Biopharmaceutical industry, USA	• Reducing process flaws • Eliminating yield variation	• Making targeted process changes according to statistical analysis • Increasing its vaccine yield by more than 50%	• Making a long-term investment in systems to collect more data • More advanced analytics
Remote monitoring application for heavy-duty equipment vehicle, USA	• Assessing and predicting the health of the diesel engine component	• Utilizing classification model to detect analogous engine behavior • Fuzzy logic-based algorithm for remaining life prediction	• Predictive manufacturing process • More comprehensive big data environment
Tata Motor, India	• Driving quality and reducing cost in manufacturing process • Increasing customer satisfaction level	• Utilizes process excellence and Six Sigma principles • Analytics of CRM system data	• Combination of optimization, emotion, and empathic use of data
Premier Healthcare Alliance (vendor: IBM), USA	• Improving patient outcomes • Reducing expenditure	• Collecting data from different departmental systems and sending to central data warehouse • Generating reports to help users recognize emerging healthcare issues by data processing	• Developing efficient unstructured data analytical algorithms and applications
General Electric (Global Software and Analytics Center), USA	• Boosting industrial product sales • Reducing after-sale maintenance cost	• Optimizing the service contracts and maintenance intervals for industrial products	• Integration with data processing in production process
Aerospace industry, USA	• Predicting number of returns in the future • Minimizing product escapes	• Combining large datasets (manufacturing and repair) together • Using predictive algorithm to analyze data in aerospace test environments	• Automated process of datasets combination

Source: Zhong et al. (2017)

Table 10 Typical applications of ICT

Industries/companies	Aims	Improvements	Future research
Nigerian national policy analysis, Nigeria	• Examining the ICT impacts on education • Determining suitable policy for ICT potential in the Nigerian education system	• Integration in teaching and learning • Improving teachers' professional development	• Maximizing ICT potential • Proper ICT implementation and monitoring
Foresight processes, Delphi, Germany	• Identifying the channels for ICT in foresight • Determining the focus on foresight processes using ICT	• More precise strategic decision-making • Increasing product variety in ICT-based foresight tools	• Insights concerning specific tools • Expanding the scope
Job satisfaction evaluation, USA	• Examining the association between ICT factors and job satisfaction • Examining technology orientation impacts	• Improving sales and job satisfaction • Integrating ICT tools in daily professional activities	• ICT-enabled training • Educational influence of ICT
Tourism, Hong Kong, China	• Establishing the process of ICT in tourism	• Improving hospitality in tourism • Improving tourism services	• Industry applications • Incorporating ICT into business missions
Water and soil monitoring, Taiwan, China	• Using ICT to efficiently improve monitoring systems • Classifying the focal area into different agricultural environmental risk zones	• Improving environmental assessments and environmental management decisions • Increasing awareness of ecosystem services	• Collecting data analytics • Increasing the potential of environmental monitoring coverage
Nursing education, Australia	• Examining e-learning with ICT • Finding the impact of ICT changes on nursing education	• Improving learning efficiency • Increasing motivation for learning	• Learning-quality evaluation • Preregistration nursing curricula
Women's primary healthcare, Brazil	• Analyzing the ICT incorporation in primary care • Identifying different aspects associated with better quality in the care	• Improving women's healthcare • Improving ICT resources utilization	• Incorporation and the quality of primary healthcare • Policies implementation
Emergency medical services, China	• Storing and interpreting data • Building an ICT system for emergency medical services	• Improving emergency medical rescuing processes • Increasing data access	• Applying standard data models • Short value chain
ICT-enabled manufacturing landscape, Germany	• Examining industry decision-making using ICT	• Improving decision-making efficiency • Improving product quality • Decreasing time-to-market	• Allocating production capacity within a value chain • Establishing a heterogeneous tool environment

Source: Zhong et al. (2017)

3.1 Industry 4.0 in Brazil and Future Course of Action

In Brazil, at the current scenario, the applications of the concepts of Industry 4.0 are still in the count of negligible, considering the number of existing manufacturing organizations and the scope to which it could be achieved in the future. As of date, many companies are in the mindset for the investment on the I4.0 specific technologies which would slowly lead to the core implementation of the I4.0 at large.

The major roadblock that is being faced at this stage is to identify the socio-economic impact. A majority of the section feels that the workforce is still not skilled enough to adapt to the new technologies, thus an abrupt implementation in near future would lead to the creation of mass-scale unemployment, which would disrupt the socio-economic aspects of a great number of people.

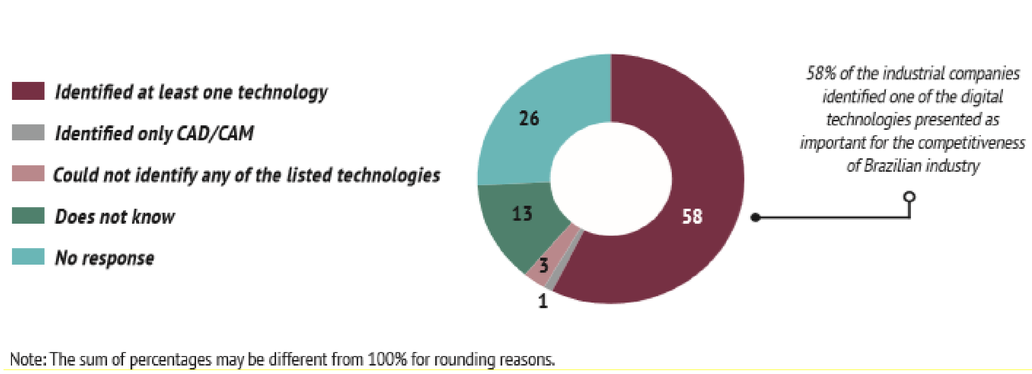
However, another faction is in favour of adopting the I4.0 because it is felt that it will urge to create many jobs in highly skilled sectors thus open up employment opportunities. But even for this, the emphasis is mostly set upon the fact that a huge focus is to be diverted towards improving the basic technical education through schools and colleges, asking for greater investment in this sector. There are many associations which are actively working in conglomeration with industries and companies in specific, to actively have further research in this direction of I4.0. The technical know-how remains another concern when companies try to implement the elements of I4.0 because not many individuals are trained at a certain desired level to create a fully functional I4.0 for specific business requirements. The training is dispersed and not focused, hence there is an issue of having close-knit progress. This concern also generates another risk for rapid implementation, because when they try to do so, shop-floor operators need to be skilled up for the new system and that seems to be a high investment risk for the companies even willing to do so, as the calculated levels of return on investment (ROI) is a grey area.

Another roadblock that has been highlighted always during the recent periods of economic crisis, is that of the affordability of the technologies by the existing companies for the transformation required towards the shift in I4.0 direction. “Most of these technologies are available, but very expensive”, notes João Alfredo Delgado, technology director at the Brazilian Machinery Builders’ Association (ABIMAQ).

Domestic companies are also making their moves. One example is Romi, which in April 2017 launched a device that combines machining and additive manufacturing–it’s the ability to mould metallic parts by adding or subtracting layers, in a process similar to 3D printing, only done using metallic powder, which was developed by a company in England. “There are companies abroad that are using that type of solution, adapting additive manufacturing to existing machining devices,” says Douglas Alcântara, product engineering manager at Romi. “Our solution is more compatible. The machine comes loaded with the technology, able to record and receive data about the processes and instantly send them to clients instantly.”

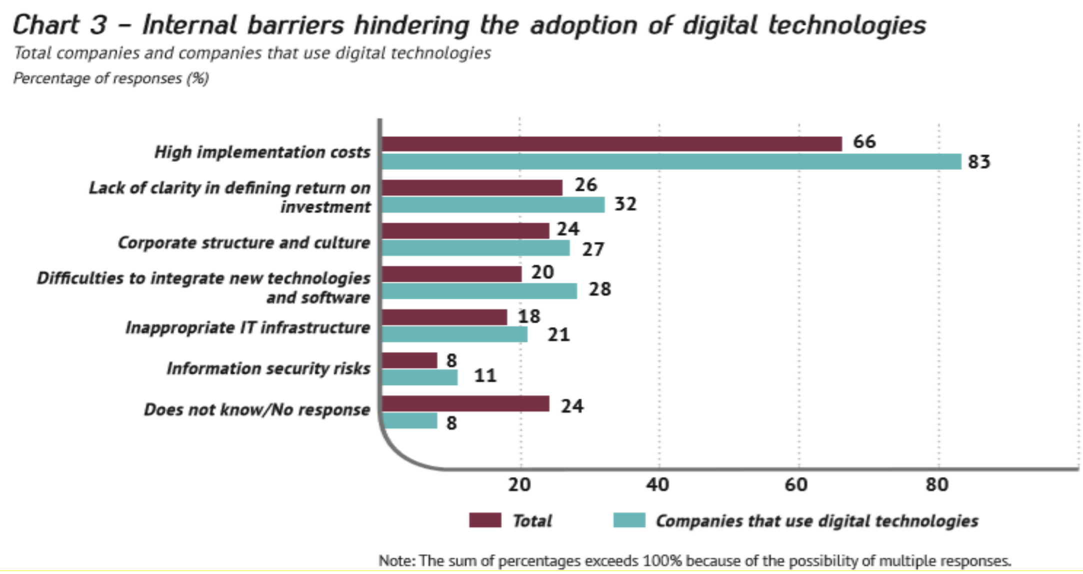
An extensive survey report was published in April 2016 by Brazil's National Confederation of Industry (CNI). Considering various aspects and excerpts from the survey termed “Special Survey Industry 4.0”, we can get deeper perspectives which are the areas that have to be focussed for improvement.

Figure 27 Low Knowledge Constitutes an Obstacle to Utilization



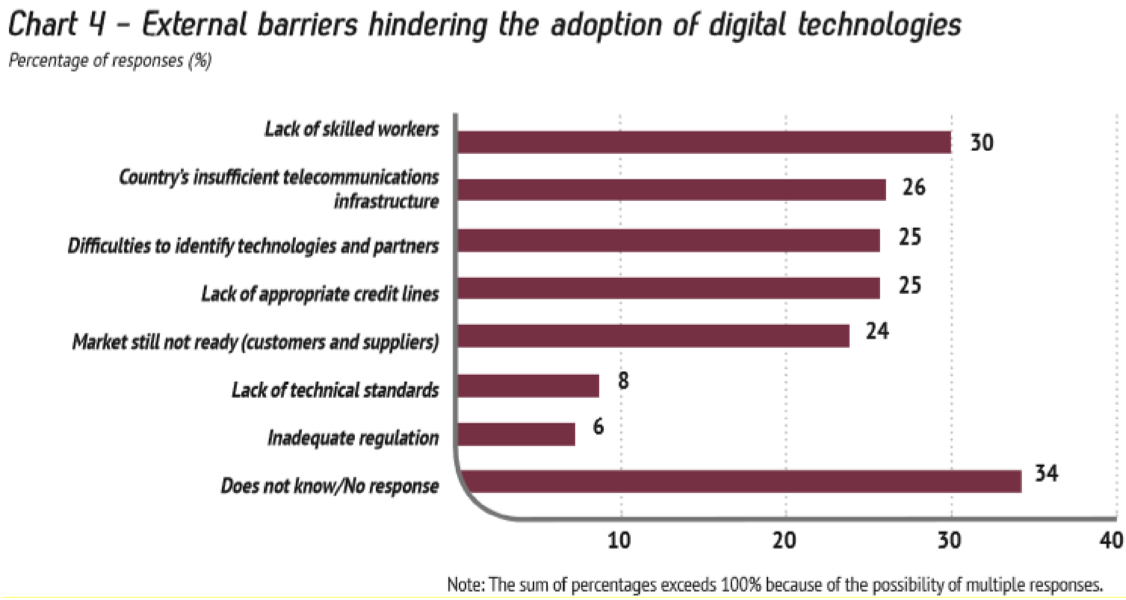
Source: adapted from Special Survey Industry 4.0 (CNI) (2016)

Figure 28 High Implementation Cost



Source: adapted from Special Survey Industry 4.0 (CNI) (2016)

Figure 29 Lack of Skilled Workers



Source: adapted from Special Survey Industry 4.0 (CNI) (2016)

"The findings of the survey show that Brazilian companies within the manufacturing sector are still in an early stage of migration to digitalization and still in the process of deploying the technologies", says Renato da Fonseca, executive manager of research and competitiveness at CNI.

As per the recent developments that the few associations are undertaking, one such is by Associação Brasileira de Internet Industria (ABII). They have collaborations from multiple universities, national forums from multiple countries across the globe, many companies as partners for learning and research and have a group of independent researchers from various sectors.

They share the common goal of increasing the pace of adoption of key features of Industry 4.0, through a systematic way and efficient cascading amongst the individuals and stakeholders of any particular organization, in a specific way as per the requirement of the business model, which could also translate into mutual adaptation with newness and need. ABII also conducts multiple events, seminars and annual meets in order to rope in the most advanced updates into the coverage and awareness of the people from the industry and the learning centres like universities.

3.2 Industry 4.0 in Italy – History and European Based Strategy

Being pioneered by Germany and termed as Industrie 4.0, in the initial days, it became the talk of the ever-evolving and efficiency seeking companies across Europe. Industry 4.0 has been identified by the Italian government as one of the strongest points for the development and progress towards the next generation of industrial activities. Thus a major step has been taken on a national basis, in the form of a strategic action plan termed as Industria 4.0. Multiple basics have been taken into account, for example, an investment in growth through hyper- and super-depreciation for assets purchased towards this cause, credits to innovation thus accelerating innovation, guaranteed funds for SME's, Allowance for Corporate Equity (ACE) and productivity wages.

About this initiative, quoting the words from Italian Minister of Economic Development, "The "Industria 4.0" National Plan will affect every step of the life cycle of companies that want to improve their competitiveness by supporting investments, the digitalization of industrial processes, improvement in workers' productivity, as well as the development of new skills, new products, and new processes."

By the end of the year 2016 and the beginning of 2017, there was an upsurge in the academic sector all over Europe, including Italy, to find ways and set guidelines or standardize the methodologies for the adoption of the elements of Industry 4.0 and create an environment for the growth and adoption of CPS. As an example to be cited, is my own university, Politecnico di Milano. Here, through collaboration from the industry and through the support from the university administration, Department Of Management, Economics And Industrial Engineering (DIG) established the IoT laboratory and the Centre of Excellence for the factory of the Future in collaboration with Siemens and IBM. This helps to attract many more research proposals from various industrial sectors thus enabling the evolution of the industry in parallel to the evolution and establishment of the reign of Industry 4.0.

A study done by the European Commission analyzed the implementation of the above plan. The main intention of this study was to understand how the various policies that were implemented were beneficial and what could be done to further incentivize the adoption of I4.0 practices. As per the report published in 2017, under the Digital Transformation Monitor with the title "Italy: Industria 4.0", gave a list of fact checks as in Table 10.

Table 11 Strategy Fact-Checks for Italian Industry 4.0

Policy Lever(s)	Top-down approach, orientation towards technology as well as skills, public financing.
Funding Model	Funding model based on public funds earmarked for implementation of specific measures in order to create favourable conditions boosting private investment in technology, innovation, R&D.
Target audience(s)	Companies and entrepreneurs, regardless of the size, sector or location.
Concepts & Focus Areas	Take full advantage of opportunities related to the fourth industrial revolution, promoting investments in innovation, intangible assets and R&D, spreading the culture related to "Industria 4.0" and developing skills.
Key drivers	Active involvement of the policy makers and key stakeholders, variety of easily accessible fiscal instruments, a strong network of highly specialised competence centers offering tech transfer services to SMEs.
Key barriers	So far, the implementation process is smooth, without any barriers and complications.
Implementation strategy	Automatically activated fiscal measures (tax incentives) on investments, R&D expenditures and IP assets, and support to the creation of network of Digital Innovation Hubs (DIH) and Competence Centers.
Results expected	> €10 bn. private investment increase in 2017/2018, +11 bn. R&D&I private expenditure in 2017-20, 200.000 academic students and 3.000 managers qualified in I4.0, doubling the students in vocational schools on I4.0 topics
Budget	More than €18 billion for the period 2017-2020.
Uniqueness factor	Parallel focus on technology and development of skills necessary for the successful digital and technological transformation. A wide variety of fiscal incentives available for companies of any size, sector and location.
Value-added for policy-makers	Active cooperation with stakeholders; international cooperation with France and Germany on I4.0 topics.
Expected Impact	New development of I4.0 skills, uptake and diffusion of new technologies, expansion of R&D activities; increasing the competitiveness of Italian companies and industry.

Source: Italy: Industria 4.0 Digital Transformation Monitor (2017)

Based on the actions and directives taken in Table 10, an array of expected results/achievements has been enlisted to be expected. However, these were the results which were understood to be in a real case scenario where the adoption might be quite less optimistic compared to what could have been planned while framing the policies and forecasting done based on them. Table 11 highlights the expected results.

Table 12 List of Expected Results(2017-2020) for Industria 4.0

Expected results (2017-2020) for Industria 4.0	
Innovative investment	• > 10 billions € private investment increase 2017/2018 • +2.6 billion € mobilised early stage investment 2017-2020
R&D	• + 11 billion € research, development and innovation private expenditure (exceeding 2% of GDP) over the period 2017- 2020
Skills	• 200.000 academic students and 3.000 managers qualified on I4.0 topics • +100% students attending vocational schools on I4.0 topics • ~1.400 industrial PhDs focused on I4.0 topics (out of ~ 5.000 included in the National Research Plan)

Source: Italy: Industria 4.0 Digital Transformation Monitor (2017)

To add on to the policies and to pace up the progress in the direction of I4.0, Italy has joined hands with France and Germany along with their respective key initiatives such as the French Alliance Industrie du Futur and the German Platform Industrie 4.0 in international trilateral cooperation. This would not just support but strengthen the digitalization processes of their manufacturing sectors.

4 COMPUTATIONAL VISION

4.1 What is Computational Vision

As a general consideration with the objective of combining *computing* with *vision*, the main idea behind this sector of research is to create the maximum productivity or output obtained from a simple vision, which in this case is from a camera. With this in the overview, the target can be two-fold, as described by T.S. Huang in a paper from the University of Illinois at Urbana-Champaign.

He says, firstly, this computer vision tries to create a tangible and quantifiable model of a generic image captured by human eyes. Secondly, this kind of image with data and information readily available for interpretation should be fed to capable systems to generate actions or orders for activities to be performed by co-related components. With refinement, the idea would be to have a system which is equally efficient or at times even better equipped to collect such information, process them and then take actions based on them. Decision making of the systems would then turn out to be more fluidic and only require less human intervention due to the constant update of learning from data sets. This gives rise to the area of Computational Vision attached to Machine Learning, Artificial Intelligence, and Deep Learning.

4.2 History and Evolution of Computational Vision

Quite stereotypical regarding the fact that the origin of new ideas generally rooted from one of the few elite maxims of best universities from this generation, during the mid-20th century, an initiative was started from MIT, by Larry Roberts, who is also popularly called as the father of Computer Vision. His PhD thesis included the possibility of extracting 3D geometrical information from 2D perspective imageries of blocks. However, this did not progress beyond this until the next major breakthrough achieved by David Marr at MIT, who did a bottom approach for scene understanding. However this famous paradigm created certain limitations, which led recent researchers to adopt more of a heterogeneous approach to give rise to the new paradigm called "*Purposive Vision*", and one of those important contributors is Yiannis Aloimonos from the University of Maryland.

The next decade was more focused on mathematical modelling, and analysis of quantitative aspects of scale and space vision, like scale-space, cues from texture, shades, colours and contours! Henceforth, moving forward there was more focus on the reconstruction and camera calibration, image quality and better input through higher resolution and pixel enhancements.

By the last decade of the 20^{th} century, a great impact on this arena came through a higher interaction between graphics and actual vision of the images, which led to better rendering of images, morphing, image recovery and image stitching for a panoramic output through interpolation of closely matched coordinates.

In the last few years, it is more into the creation of the state where there is a higher focus on the recreation of the correct image and hence being able to recognize the exact object within the frame specified through feature-based methods, thus resulting in the capability of faster processing of data and generating almost real-time inferences. However, there are certain major drawbacks, the primary one being the possibility of having a good value of correctness over a consistent period.

4.3 Computational Vision and Deep Learning

The area of Computer Vision would not have achieved the stage at which it is now, if not for the application and infusion of the principles of deep learning (DL). Now let us have a look at what basically is achieved by applying DL to Computer Vision. For this, the basic requirement is to create a huge database of images and to train and manufacture the algorithms required for future utilization. It, however, is not a static set of database, but based on the next result, it gets automatically updated to increase the probability of detection through having the finest possible line of tolerance while analyzing and detecting of an image. This also lets users create various segments and contexts and scenarios based on which the entire learning process of the algorithm changes, leading to a unique and specific result-oriented application.

So let us have a look at how Deep Learning helps in the evolution of Computational Vision. DL actually tries to undertake automatic feature detection, generated an end-to-end model with high details of data sets, allows for the re-use of models by feeding the data sets into the trainer system of the library of the deep neural networks, thus, generating superior performance and always keeps itself updated for an improved performance the next time. The salient of all of the above is that it uses a very general method for the usage of the CV system for the most complex processes. There are various types of neural networks that are popular for the purpose of image analysis, like Convolutional Neural Network (CNN), Multilayer Perceptrons (MLP) and Recurrent Neural network (RNN). However, CNN is the most used, while MLPs are used for image layer extraction from CNN based pattern or library and RNNs are used for pattern or image study from video files.

Nowadays, there are multiple fields where the DL has been applied with quite good success. Some of them are Optical Character Recognition, Image Reconstruction, Image Super-Resolution, Image Classification, Object Detection, Face Detection and Face Recognition.

4.4 Computational Vision: Working and Popular Tools

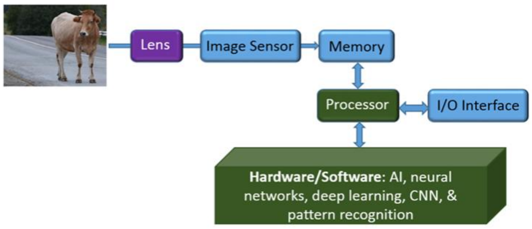
Computational Vision (CV) works using the following six principal functions, namely:

a) Image Acquisition: To use the lens for capturing a digital image of an object in the target.
b) Pre-Processing: This results in refining the image for a better understanding of the image in context and extract the maximum information out of it.
c) Feature Extraction: This process results in an almost recreation of the digital image into a set of information which in turn could be used by the learned set for a match.
d) Segmentation: A set of specific information are then segmented and matched, delivering a result of preliminary level identification/detection.
e) High-Level Processing: Narrow down on the segments by raising the precision level for having a closer match for the extracted data points.
f) Decision making: After the above method, a result of required nature is displayed, which could range from a pass or a fail checks, correct visual recognition or further complex results.

So basically, it is made up of the 3 fundamental elements: A camera, hardware, and software. As in the figure below, we notice that a major important task is being performed by the processor, which initiates the interaction between data sets trained and updated by AI, CNN and Pattern Recognition.

This processing is done these days in the cloud in order to avoid the requirement of large size local processing centres, there is a shift from the local onboard processing towards the finesse of Internet of Things(IoT), hence performing inference analysis over the cloud. The use of the Graphics Processing Unit (GPU) is getting replaced by Field Programmable Gate Array (FPGA).

Figure 30 Components of Computational Vision

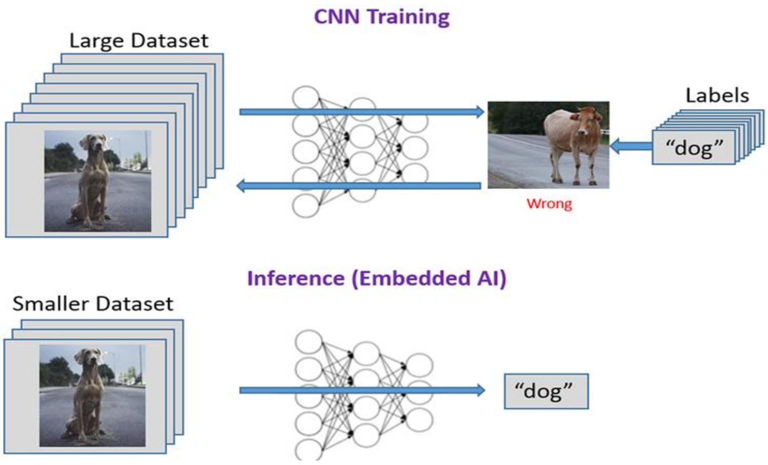


Source: Agarwala (2018)

As we speak here, a very level of expertise and knowledge of complexities in the research in the area of CV has been reached. This has been made feasible through the application of the concepts of DL and CNN. And all this has happened mostly in the last six years.

While talking about CNN, Badru Agarwal in his blog defines that CNN Training is a very exhaustive process and requires a huge amount of time as it scans through a large data sets creating a wide array of mapping of integer points. On the other hand, CNN Inference making procedure is very rapid, also sometimes real-time, thus uses less amount of such data sets and provides a result using fixed-point integers. He shows the difference between them in the following figure:

Figure 31 CNN Training and Inference in Computational Vision



Source: Agarwala (2018)

He then talks about the very present day technique called the High-Level Synthesis solution, which is used on a platform called the HLS Catapult platform thus leading to a very effective real-time image processing and identification.

There are popular CV tools and libraries that are generally accessed by programmers while creating the algorithm for any specific project. Some of them are OpenCV, Matlab, AForge.Net, TensorFlow, and CUDA. SciPy and NumPy, based on Python are very powerful tools that are being used. In our study case, our partner MVISIA has mostly been using Python.

4.5 Example of Applications in the Real World

The actual use of Computational Vision has been started for a long time and in various sectors in commercial ways. This could be in the form of virtual reality or even augmented reality. Not necessarily all the applications are just analysis, but even some applications are to even to create an experience for the viewer or end-user, thus leading to enhanced efficiency for a specific purpose. To enlist a few of them:

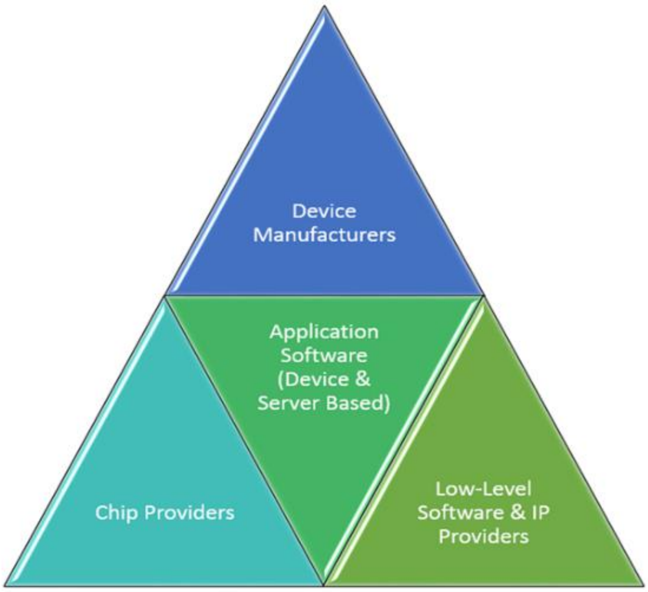
a) Manufacturing;
b) Military and security/surveillance;
c) Health;
d) Space exploration;
e) Agriculture;
f) Sports and Entertainment;
g) Marketing; and,
h) Retail stores and outlets.

Many organizations have exploited this in their operational benefit:

a) Autonomous vehicles (Tesla, Volvo, WayMo etc);
b) Google Translation application;
c) Facial recognition by many applications and smart devices;
d) Security/Surveillance/Monitoring purposes by organizations and countries;
e) Kinect for Windows retail clothing scenario, AmazonGo for self-shopping experience and StopLift for preventing shop-lifting/theft cases; and
f) SlantRange uses for efficient pesticide and nutrients application on fields by drones.

From one of the studies done by Tractica that there is now a complete ecosystem of product development based on the usage of Computational Vision. The significance of this finding is that, although there is ample scope of further improvement in technologies and applications, now there an arena where there is a scope for a complete involvement and application of a system specific for a given requirement. Thus, it is not just beneficial for the manufacturing industry, but it incorporates the application of this technology of CV for collaborating multiple sectors seamlessly in order to provide the most optimized services to the user.

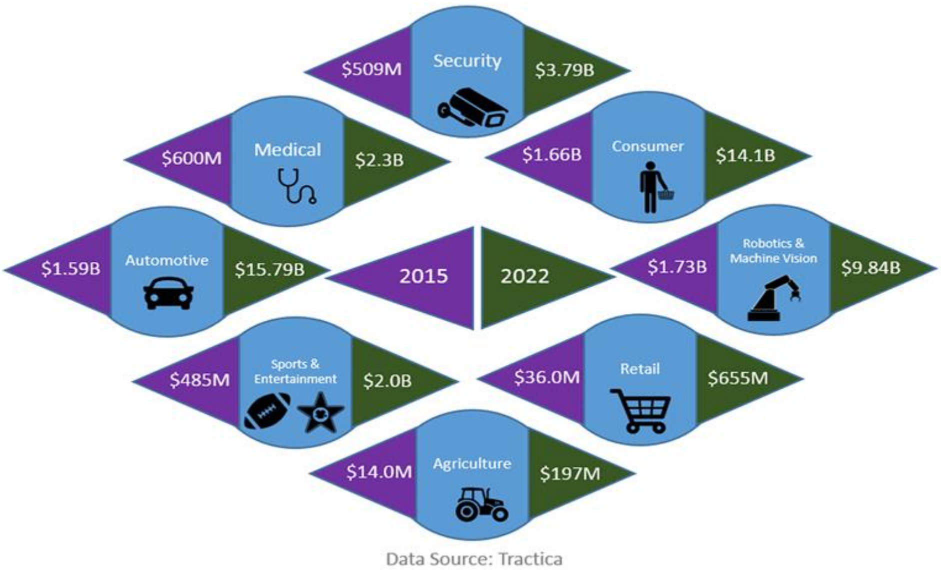
Figure 32 Ecosystem for further development of Computational Vision



Source: Agarwala (2018)

Computational Vision has found a very wide array of applications all over the globe, starting from very basic to highly complex and secured situations and sectors. The same paper also goes on to say, to identify the trend and trying to predict the amount of revenue generated by the application of CV in various sectors shows a very interesting and alluring fact.

Figure 33 Revenue from the Application of Computer Vision in Different Sectors



Source: Agarwala (2018)

4.6 Computational Vision in Industry 4.0

In achieving all the above-mentioned aspects of the benefits of Industry 4.0 and its smooth functioning, there has to be in place a wide variety of sensors and monitors. And one of such an active monitor could be the computational vision applications.

So when we refer to computational vision all that comes to mind is from our past experience from the famous Sci-Fi movies! And quite precisely so that we are right in thinking about it. It is actually considered one of the most effective feedback loop system that an integrated I4.0 system could possibly have. There are multiple reasons for this consideration. First of all, we must try to understand the actual architecture of a computational vision system. Then it could be made clear on how this system could be effectively used for the purpose of the integration of the digital system of shop floor control with that of the physical shop floor of a factory. This is not the end of its usage.

Because the most important part of this system being the capability of this system for allowing the entry of human intervention as and when required for the sake of critical decision making, extreme case adjustments and change of system requirements from time to time due to evolution or modification of design of the product as well as the assembly line itself. Hence this ability guarantees the specific system to be always in sync with the required outcomes by a control well established through computational vision.

However, to understand this a bit in details we need to focus on what has already been researched with this technology based addition to additive manufacturing and what are the findings from various sources towards this cause.

There has been a lot of research work done in the field of academics that contributes to the study and application of computational vision, however, we will be going through a few specifics which are based on the scope of our study. However, it is worth mentioning, that far more effective strides in the recent years and months have been taken by few companies who have worked with audio-visual technologies and also with various augmented reality and cloud-based visual computing and technical solution based product. This not only demonstrates the utilization of Visual Computing but also how popular this area of research and investment it has become in recent times. And relentlessly, the companies are taking great efforts in maximizing the potential usability of this technology to facilitate a variety of solutions, making them economically viable and a great alternative to many manual based tedious or critically risky task being replaced and effectively being taken up by computational vision, which in return facilitates humans to take control of the actual activity from a more comfortable ambience, mostly remotely, thus not only effectively enhancing human productivity but also reducing the human health hazards and errors of operations.

4.6.1 Computational Vision: Development in Industry 4.0

In a very elaborative paper by Toro et. al (2015), mentions that there is very certain and strong spurge in the direction of industrial and manufacturing core competencies towards the maximum utilization of ICT and in line with ICT's growth and sophistication.

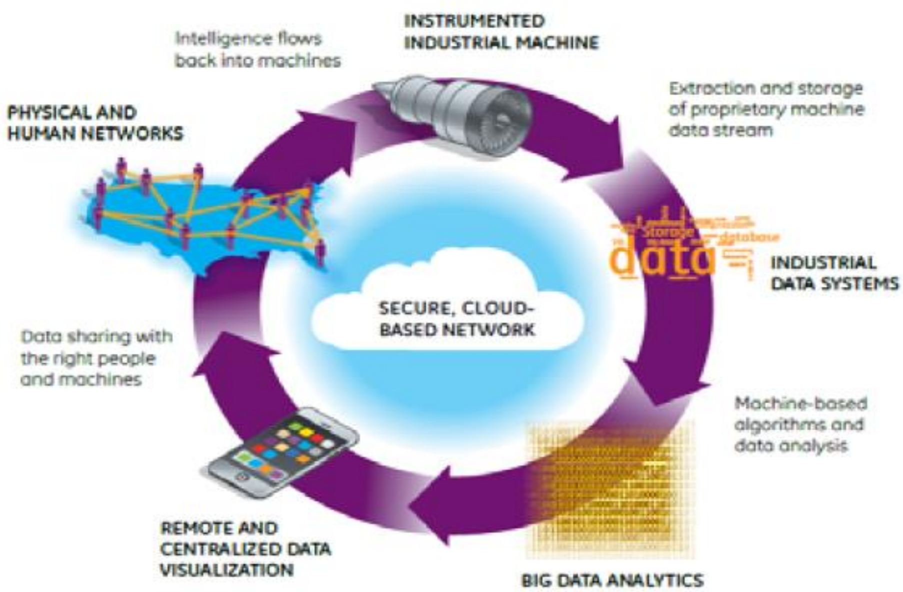
Figure 34 Visual Computing and its role in Industry 4.0

Source: Toro et al. (2015)

This not only provides an enhanced outcome of higher productivity but also leads to greater efficiency in monitoring and control of the shop floor activities. It continues to explain continues to write how the application of Visual Computing techniques have a great role to play in the effective synchronization of the physical and digital world of production in the era of "Internet or Cloud-based Production" system.

In this context, the paper extends to say that Visual Computing is considered to be the scope of acquiring, analyzing and synthesizing visual data through the collective means of visual capture tools and computers. Visual Computing, Computer Graphics and Computer Vision are the major tools which seem to play a major role in this task (Human-Machine Interaction). In order to demonstrate on which part of the Industrial internet model there would be a role for Visual Computing, an image from the company GE's paper widely accepted at NSF I/URCC Center for Intelligence Maintenance Systems (IMS) and few other industrial sectors, was portrayed.

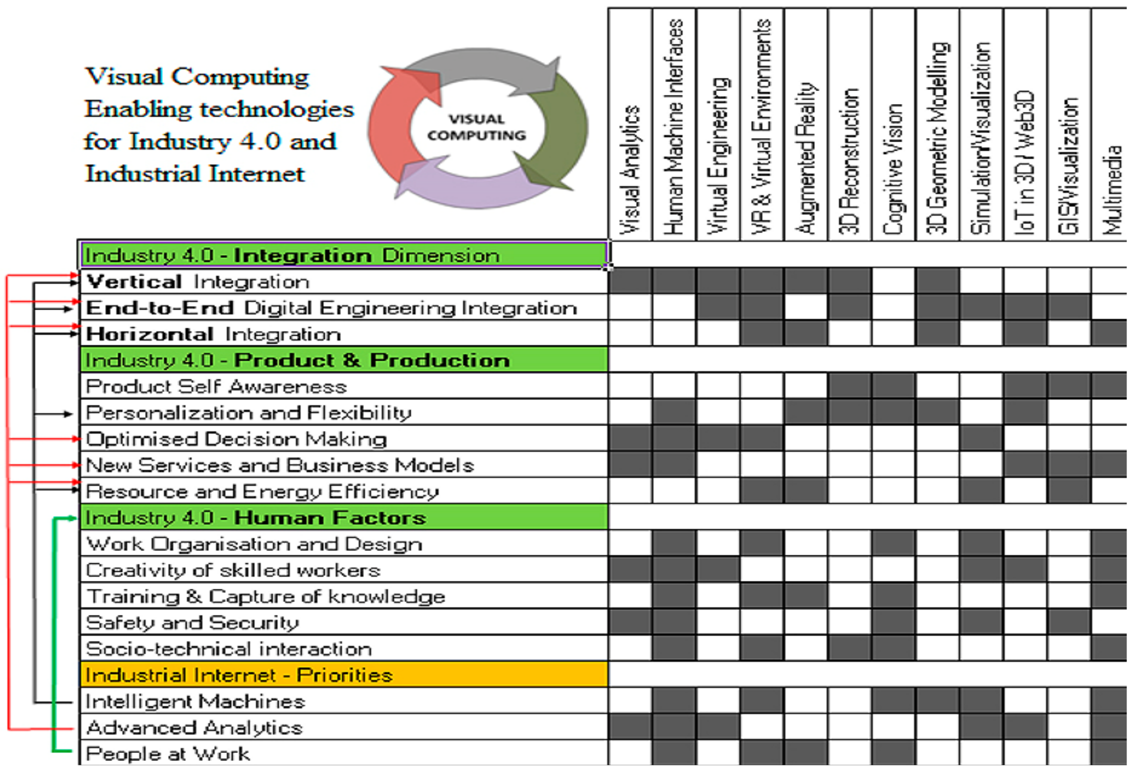
Figure 35 Flow of Information in Industrial Internet Loop



Source: Industrial Internet data loop - General Electric (2015)

Thus actually from all of this discussion, it seems to be a very potential enabler for the implementation of a smooth operating I4.0. Thus while trying to understand the relevance of Visual Computing enabling technologies, the paper shows a mapping of the parameters, techniques and importance and it revealed the following:

Figure 36 Computational Vision Enabling Technologies in Industry 4.0



Source: Toro et al. (2015)

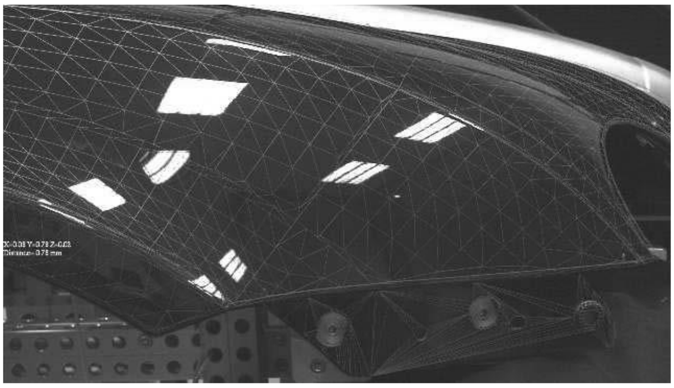
4.6.2 Computational Vision and Augmented Reality in Industry

Eminent researchers and technology forecasters have always believed in the facts that enhancement in the field of Computational Vision and thereby progress towards much more sophisticated version of application termed as augmented reality for the application on the area of I4.0 is very much a direction towards which the industrial sector is heading towards. And this belief has also lead to a lot of experimental trials in real-time applications leading to a great array of probability to implement or apply augmented reality for the shop floor activities. These applications can have a range from assembly line guidance to operators, to perform quality control check, to monitoring product coherence to agricultural activities, to maintenance operations of heavy machines and with the criticality of the work environment.

Augmented reality is more common these days with digital games played on mobiles, consoles or even using simulation setups with large size monitors. However, with the benefits and possibilities of utilization of the same being seen in the manufacturing sites, there are a lot of probable applications that are being tested.

One of them is that of testing errors in metal body shape while stamping process or in paints in the automotive sector, in the form of a comparison tool. In Figure 38, we can find that just using the method of projection rendering of wireframe pattern of the actual design on to that of the physical part, we can have a measure of the deviation if any and also the extent of error, which could further be utilized for reverse engineering process.

Figure 37 Vehicle Fender with augmented Design Data



Source: Nölle et al. (2006)

5 PROPOSED SOLUTION

In line with the target of this study, the primary tasks were divided into four stages, which were completed in various sub-stages:

a) To identify using camera vision, the assembly process in a particular work station.

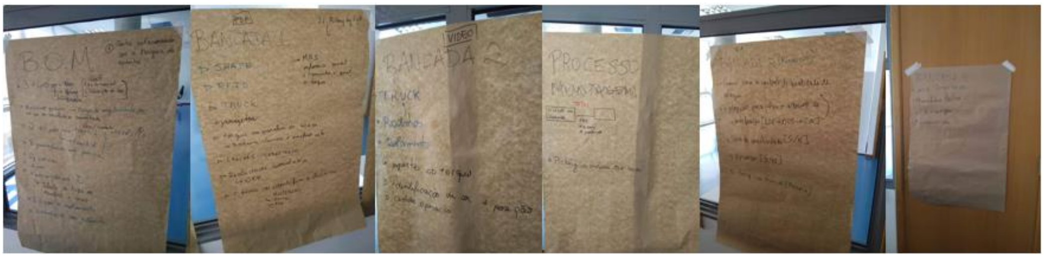
b) To establish a reference point of vision for the camera during the assembly process.

c) Identify the location of the wheels being mounted to the skateboard.

d) Identify and display on a monitor, with/without the demand of an operator of that workstation, the colour of assembled wheels.

This was actually attained after the meeting done during the first week of August in 2018. Below, Figure 39 is actually a snap-summary of primary planning for the FF. This, however, had a series of iterations after realizations of roadblocks to implement them. And finally, we came up with a plan, which is explained further in the later part of this section.

Figure 38 Initial Plan of Proposed Solution for Fabrica do Futuro



Source: from author

The proposed solution in this specific case revolves around the utilization of Computational Vision to enhance the assembly line processes as has been outlined for the purpose of a skateboard having a smart IoT box. This proposal comprises the hardware and the software involved for the purpose of having a fully functional computational vision kit. Let us have a look one by one at the hardware and software requirements:

a) Hardware:

   i) High Definition camera fabricated and implemented by MVISIA;

   ii) Circuit board for the camera-box;

   iii) Power source for the camera-box to function.;

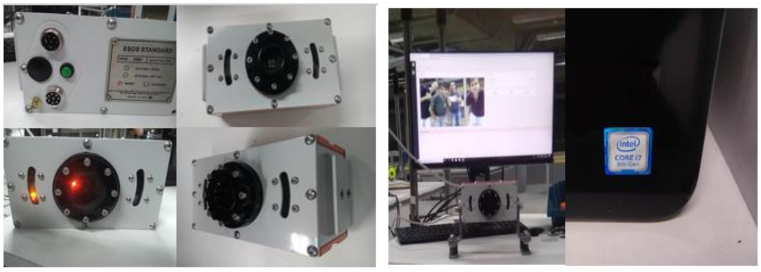
   iv) Connectivity through LAN wire;

v) Display monitor for the camera to demonstrate; and,

vi) CPU for the operation of the camera-box through the MVISIA interface.

A few images of the hardware in use has been shown in Figure 40.

Figure 39 Camera & PC-Monitor for Workstation 2 of Assembly Line



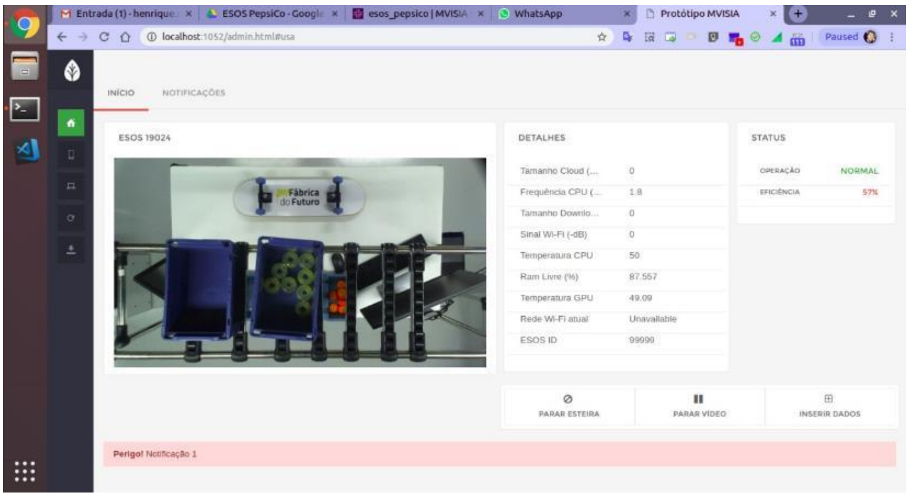
Source: MVISIA & Fabrica do Futuro (from left to right)

b) Software:

vii) MVISIA Cloud-based interface for the user/operator; and,

viii) PPI-Multitask background programming.

Figure 40 Software Interface



Source: MVISIA Cloud-Based Interface

Now, to achieve the smooth synchronization of the entire digital visual computing and physical assembly, it was necessary to have an organized workflow based on the pre-requisites. So the tasks we divided into sub-tasks which were carried out not just in a serial manner but in a parallel way handled by different teams, including members from the FF and also from the organizations.

Certain activities were being done by the team in the FF while certain activities which were possible to be evolved in the back-hand, were taken care of in the offices of MVISIA and PPI-Multitask. The list of the tasks and how the evolution of the implementation of computational vision happened in the FF:

a) Collection of images of the skates with a maximum number of iterations including the four patterns of wheels that are being used. This helped in the training of the machine program to be able to identify whatsoever be the error and colour combination.
b) Programming for creating the cloud-based interface to be installed at the FF was done by the team of Henrique, MVISIA.
c) MES was created at the background by the team from PPI-Multitask.
d) Installation of the camera.
e) Alignment of the workstation with respect to the fixed camera and focus position.
f) Install the Server location of the interface.
g) Check the image area that was being focused on.
h) Re-Map the area by creating a different base for the support of the skateboard.
i) Perform the primary camera check for its functionality and properties check.
j) Create a control parameter for the camera in the software to allow for the capture of a good quality image because the purpose of the study was to check for the colour of the wheels, thus the R-G-B values, White Balance, Contrast and Brightness adjustments were an integral part of this primary trial.
k) The second set of trials were conducted by making some adjustments in the camera properties, but there were still some errors with the constancy of identification. The solution was soon found out to be making a reference of the image that has to be monitored, thus a reference area from the skate-board was selected and this was used to plot the distance between the corresponding wheels at all four positions. An important part of this activity was to have a very stable base for the skateboard to be balanced rigidly for the camera to have an exact height for the base to ensure the required distance between the camera and the skateboard. This was achieved with a compost-wood board structure carved out of laser machines for precision.
l) Once the focal area was fixed, it was decided to have a focus on the colour of the wheels. It was a major hurdle in terms of recognition as the external ambience of the factory had a role to play in the light saturation thus it was a set of fine adjustments of the camera which helped in the major rectification of this concern.

m) With the properties set and the position of the skate-board fixed, there was a now the phase of tagging the wheels in the programming software and also the display of colour as per the positions tagged.

n) It was decided for the following logic for the display of the colour:

Table 13 Planned Colour Tag of Wheels

COLOUR OF WHEEL	COLOUR DISPLAYED ON MONITOR
Orange Wheel/Absence	Laranja/Branca
White Wheel/Absence	Branca / Branca
Green Wheel/Absence	Verde/ Branca
Blue Wheel/Absence	Azul/ Branca

Source: from author

o) This is clear from this table that the wheels had their original colour code displayed, however, any absence of wheel represented white too. The reason for this was that the background of the skate-board, on which the camera is focused, is white. Hence, in order to cope with probable confusion, the standard working procedures of this station is fixed as follows:

   i. Mount the skateboard with trucks on the jig of the station, with the logo of "Fabrica do Futuro" on the skate, facing the camera located directly over the station.
   ii. Fit the wheels in the sequence given below.
   iii. Check on the monitor for the "Send" button on the interface of the software Postman. This sends a request for a colour check to the server.
   iv. Check if there are any colour mismatch once the same is being displayed on the MVISIA interface.

p) Once this primary step was achieved, there were two more fine touches that were being incorporated within this system.

   i. To display colour of the wheels of the skateboard only when requested through another gateway interface for this purpose, which not only displays the colour on the monitor, but it also declares in the background of this interface the codes of the tagged wheels, their locations and their state of OK/NG.
   ii. To incorporate in the Interface of MVISIA the capability to also manually adjust the camera input properties in order to have better control for the case of high fluctuations from the ambience.

q) Display the colour to confirm the required specifications and to confirm the progress of the skateboard on the assembly line towards the next workstation.
r) Based on the result obtained, the go-ahead of the assembly is undertaken, which is the skate is then mounted with the nuts.
s) The skate is then passed on to the next station which involves another step based on quality control, that is the nuts are tightened using a torque meter.
t) The current state is that we have a fully functional and well-synchronized workstation designated with Computational Vision supported assembly operation.

6 DEMONSTRATION

This part of the paper deals mostly in the representation of the results that were achieved at the FF. Here I would like to cover all the stages in which the installation of this station was achieved and how the computational vision was made ready for the implementation in the assembly process.

6.1 Installation of Assembly Line of Fabrica do Futuro at INNOVA-USP

The program of Fabrica do Futuro was officially commenced with a meeting with multiple stakeholders and was initiated around the middle of August 2018. At this point, we just had a shop floor, with just the basic amenities like the connections for power sockets, LAN, air-conditioning and the possibility to install a system for compressed air operated machinery. Slowly this factory was set up by our team from FF, wherein the workstations were installed first.

Figure 41 Workstations Ready to be put on the shop floor

Source: Fabrica do Futuro, INOVA USP

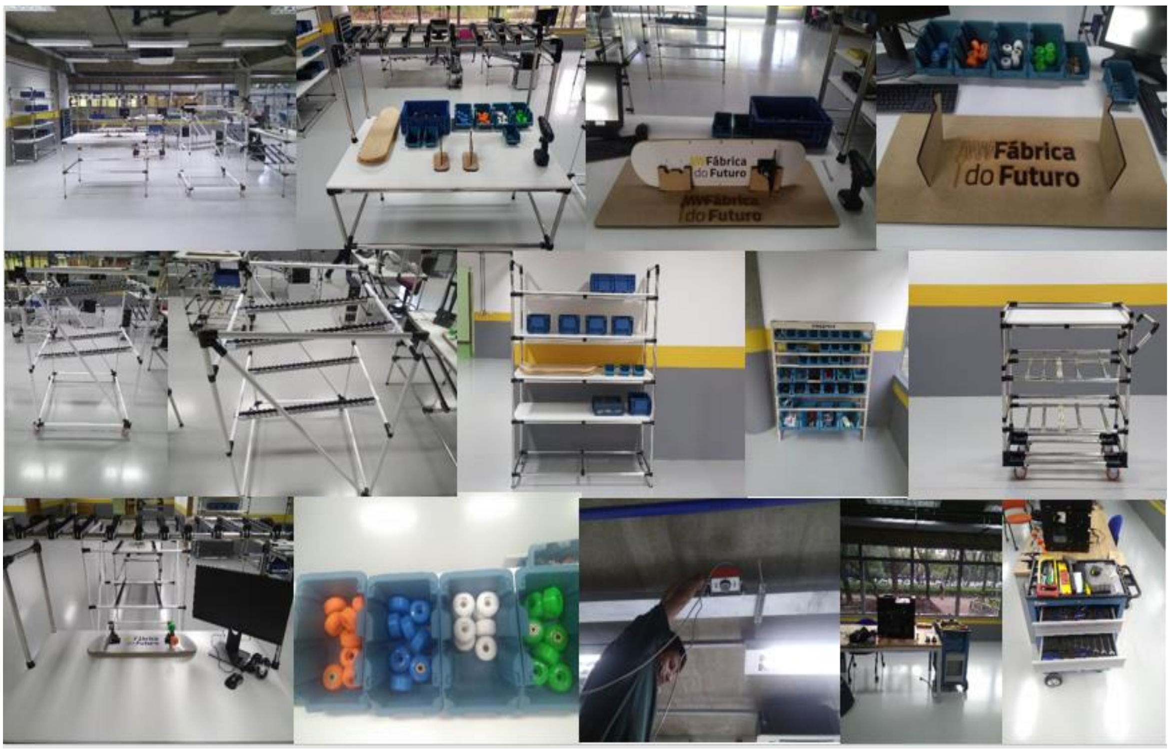
The floor plan was another critical part of this process to, in order to respect a multitude of factors like space allotted just for this assembly line, proximity to the incoming materials like distance form 3D, the ambient lighting conditions of particular workstation, ease of material flow in the production line, placement of camera and its reach to network, amongst the few.

Figure 42 Initial Shop Floor Plan of Fabrica do Futuro

Source: Fabrica do Futuro, INOVA USP

Then came the stock keeping racks which were assembled, portable large size tool kit and then we procured the 3D printers. The next step was to procure the materials required for the skateboard assembly. Thus in came the boards, with fine imprints of the logo of the factory, the trucks matching the board and then the wheels. Finally, we procured the nuts and bolts required for the assembly line. Each workstation had a particular activity, thus there are specific jigs and fixtures which were prepared for the purpose.

Figure 43 Various Components and Setting Up of Fabrica do Futuro



Source: Fabrica do Futuro, INOVA USP

6.2 Installation of Workstation 2 for Computational Vision Application

Once this was ready, we were ready for a go-ahead to focus on the specific area of study, that is the installation of Computational Vision with the support of MVISIA. The primary task, as we defined before the process of a CV system setup was to have a large database for having good training for the algorithm. Thus around 150 images of the skates with the trucks and the wheels on with multiple iterations and combinations were taken and sent to the team preparing the algorithm.

Figure 44 An Array of Images for Algorithmic Training of CNN

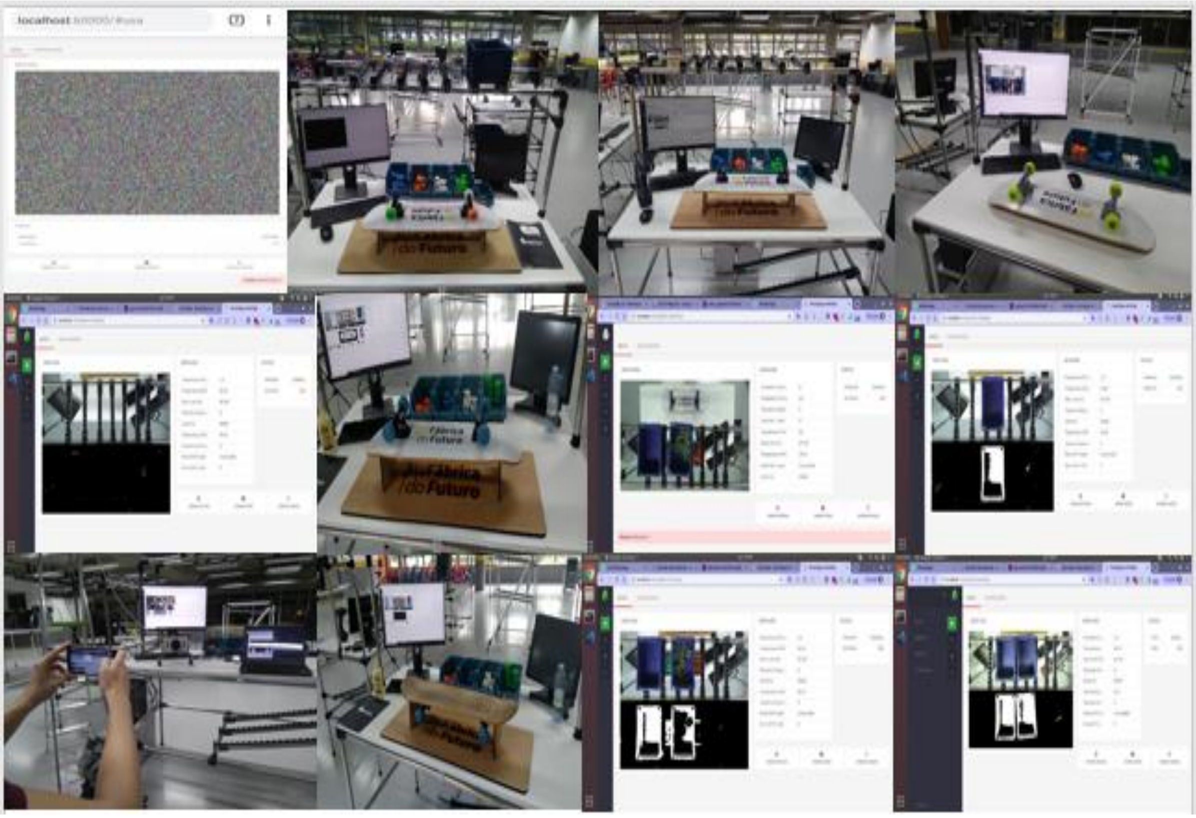
Source: Fabrica do Futuro, INOVA USP

6.3 Camera Set-Up and Primary Trials

Once the primary learning completed, we were ready for the first set of trials. The camera was installed and then we performed the first set of trials. Results were as follows:

a) Good outcome: The camera had good clarity but did not have a reference point to focus within the area captured by the lens.
b) Bad outcome: That the algorithm was not able to identify the colours.

Figure 45 Result of First Set of Trial



Source: Fabrica do Futuro, INOVA USP

The team from MVISIA did some remote study through server-based outputs from the FF and came to 2 conclusions. The number one being, the location of the jig must be fixed and cannot be displaced and most importantly, the jig has to have a background other than the colour of the surface of the skateboard facing the camera.

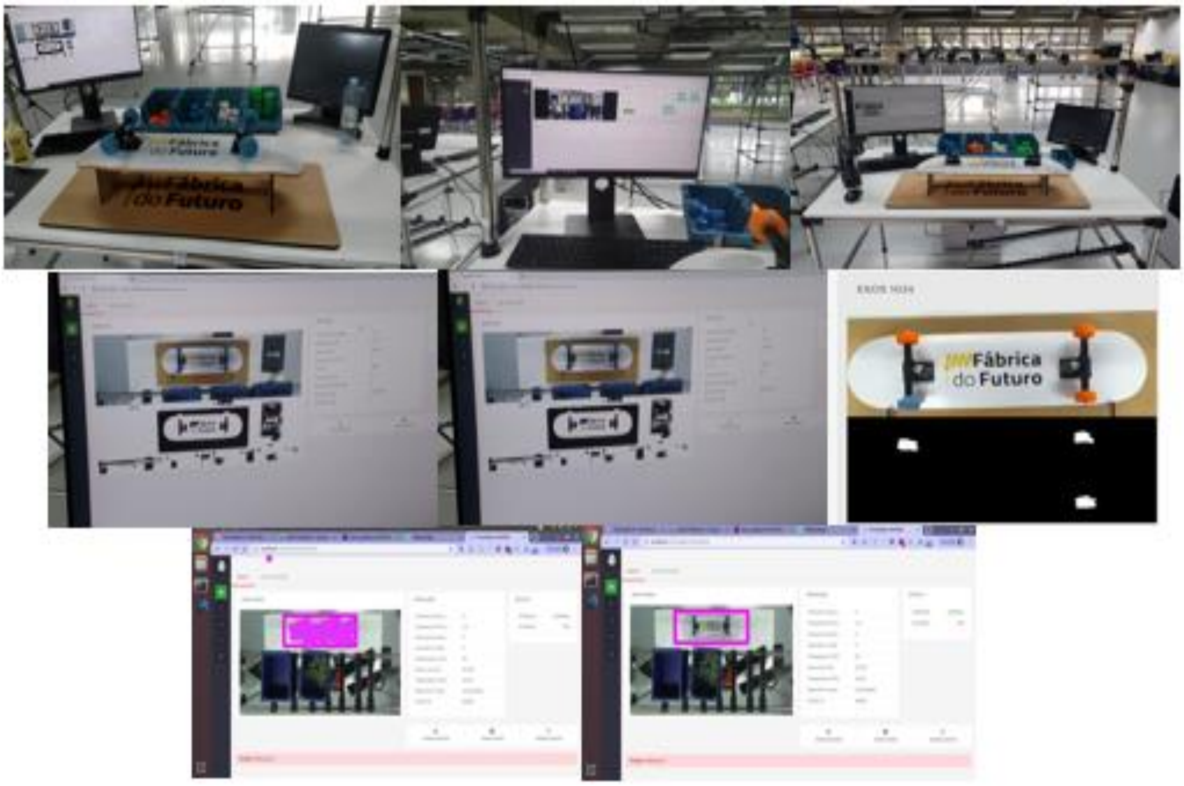
This was due to the fact that for the camera to identify the board as a separate entity, the colour of it has to be different. Hence a separate jig was created. And a fixed position was identified for mounting the skateboard.

6.4 Secondary Modifications and Trials

After this, the next trial was conducted and turned out to be quite satisfactory. The following were the observations:

a) Good outcome: The focal point was found, that is it was fixed as the logo on the skateboard which was being assembled at that workstation at that moment.
b) Bad outcome: The colours were not correctly identified at all times.

Figure 46 Second Trial Sets for Computational Vision



Source: Fabrica do Futuro, INOVA USP

Some salient points could be noted from this set of trials. They are:

a) The wheels were identified as distinctly different entities.
b) There was a concern with the logo identification for creating a reference datum.
c) It was important for having the base of the jig to be of a different colour as it impacted the recognition system due to the variance in contrast.
d) Significant changes could be observed by just having slight modifications on the Red-Blue-Green(RBG) and brightness or contrast.
e) Pattern recognition is quite dependent on the parameters set for the learning system, which in turn tracks and learns exactly the parameters required and ignores the rest.

6.5 Final Modifications and Trials

Some final modifications with the camera calibrations were done and the next trial was done. This trial proved to be the best trial with great outcomes. Following are the major observations:

a) All the colours were correctly identified, having a background position tagging and hence was dynamic when there were any changes being made.

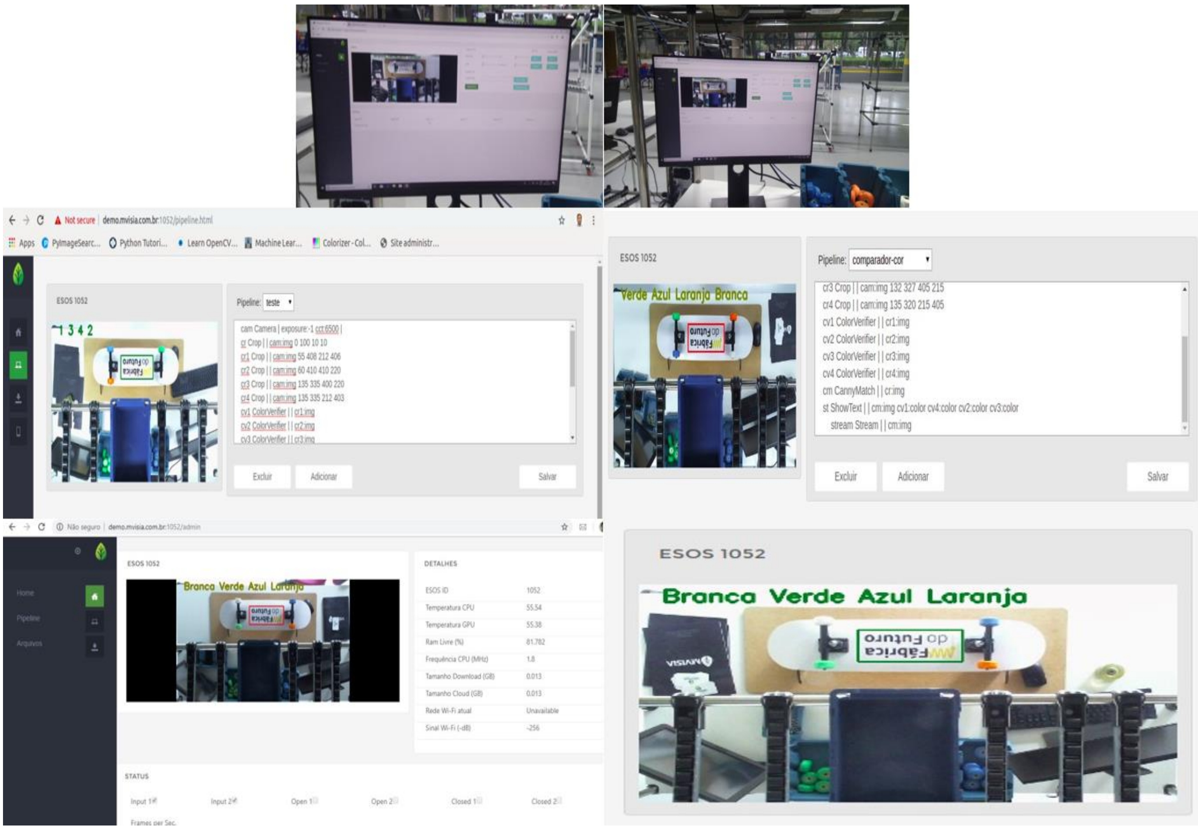
b) The display of the colours was set to be of two types:

   i. Called for by a request button using another interface called Postman.

   ii. Always displayed.

c) The settings of the camera were made available at the interface of MVISIA, enabling the user to change and adapt the camera and calibrate it based on the surrounding ambience, which meant an extra edge while allowing necessary human interference.

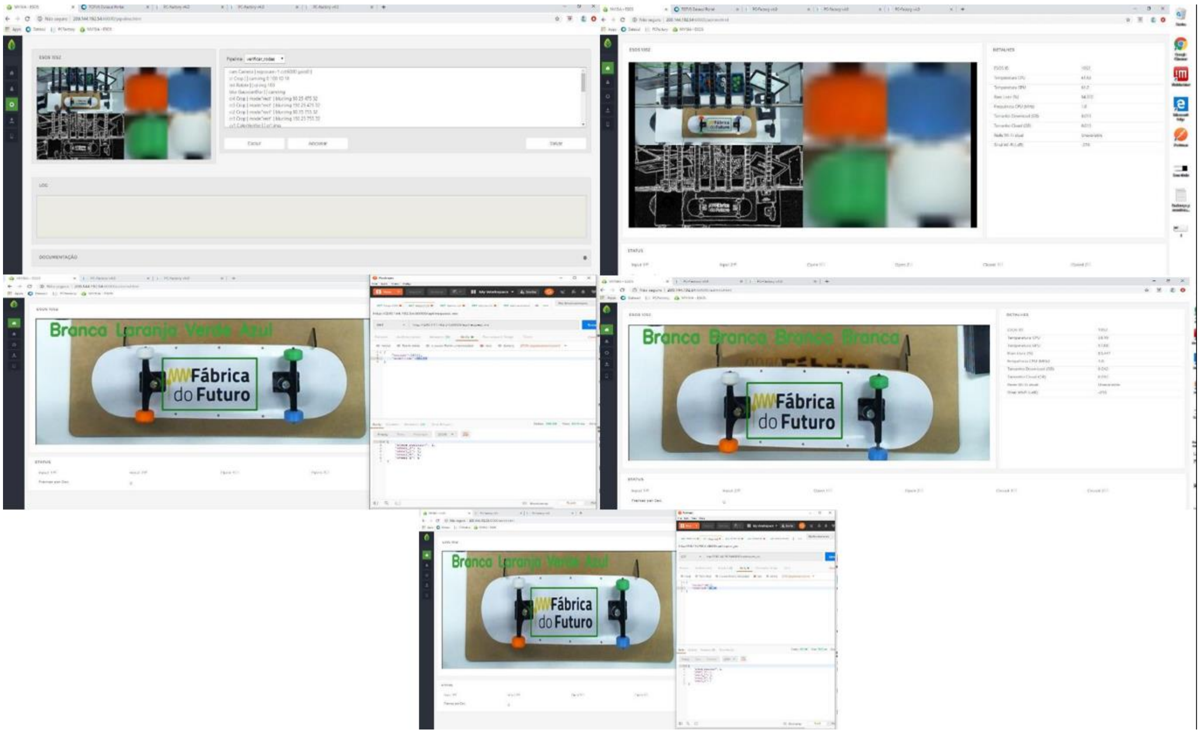
Figure 47 Results from the Third Trial (final)



Source: Fabrica do Futuro, INOVA USP

With few further iterations and some fine-tuning of colour balance and recollections of data from the interface, we came to the conclusion of the following set of images.

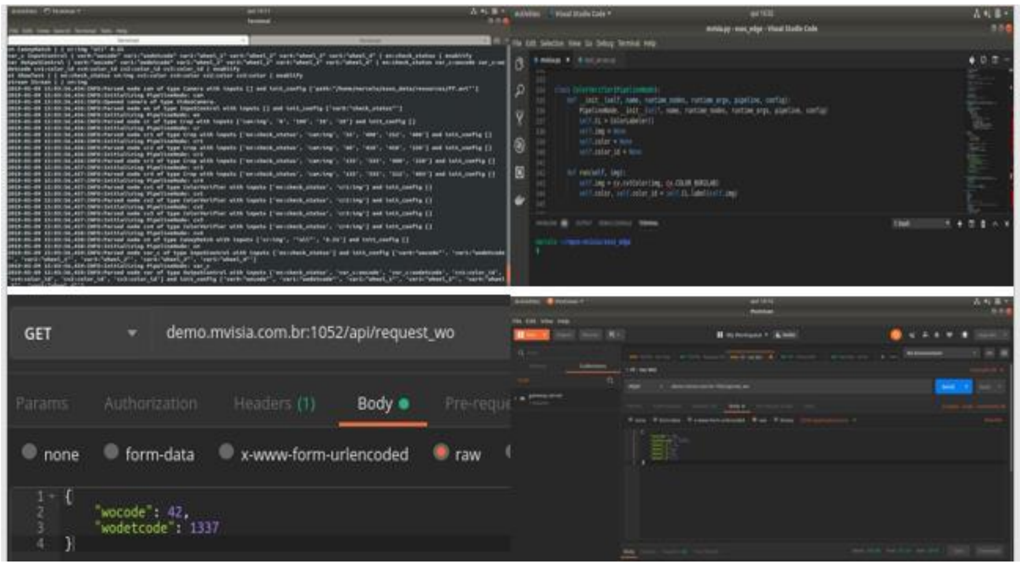
Figure 48 Refined Images and Sharp Details



Source: Fabrica do Futuro, INOVA USP

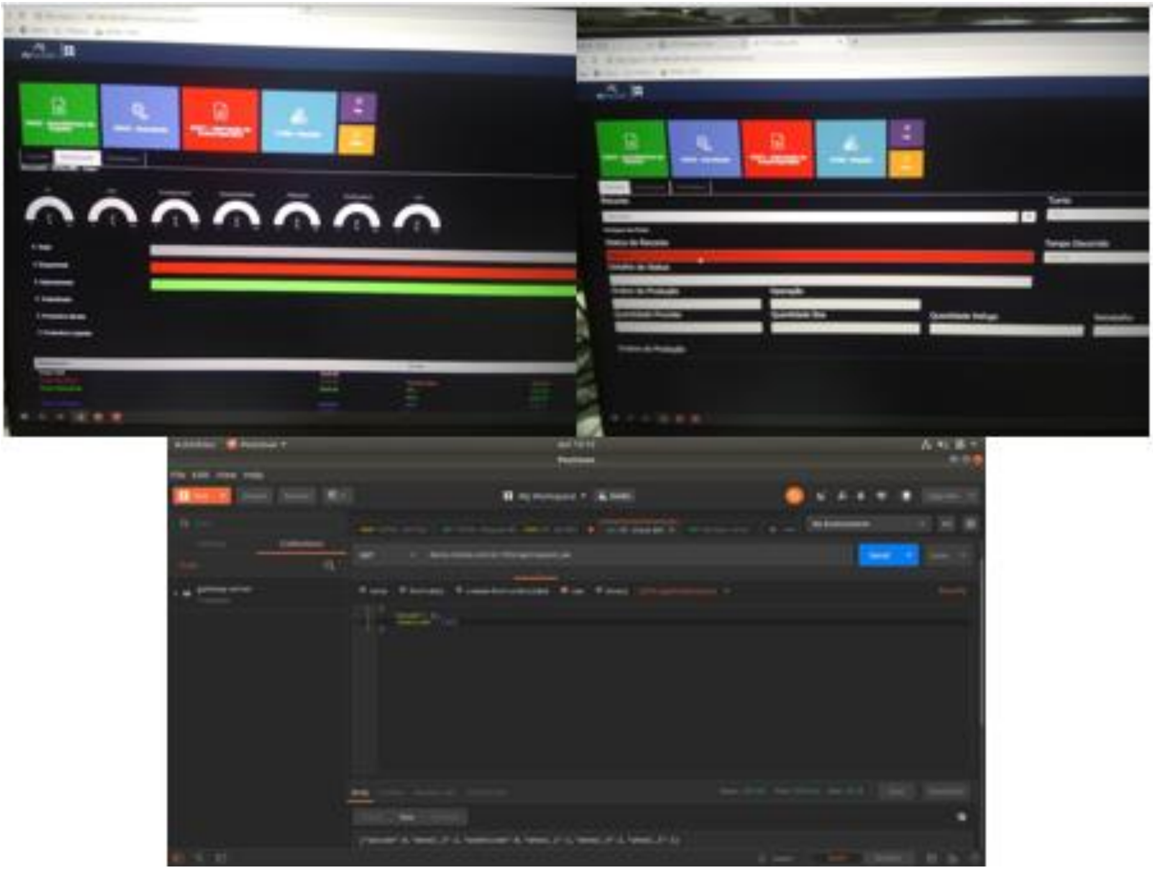
The following are the list of images which also shows various aspects of the interface, like the background program screen, the different logic operations which happen at PPI-Multitask back-end and multiple iterations which gave no errors.

Figure 49 MVISIA Interface Programming Interface



Source: MVISIA Interface, Workstation 2, Smart Skateboard Assembly, INOVA USP

Figure 50 PPI-Multitask MES Interface



Source: MVISIA Interface, Workstation 2, Smart Skateboard Assembly, INOVA USP

7 CONCLUSIONS

7.1 Evaluation

The evaluation scope encompasses the level of functional operability of the computational vision for the purpose of identification of wheels' colour. Let's have a look at the major points of evaluation of the study that has been undertaken:

Serial N°	Activity	Status
1	Check the installation position and camera functions from MVISIA hardware	OK
2	Check for MVISIA Interface	OK
3	Check for Colour Identification	OK
4	PPI-Multitask system communication with MVISIA system	OK

Source: from author

Based on this evaluation, we can identify that the objectives of this study were met and accomplished at the FF with the support of technical partners.

7.2 Future Scope

Apart from what has been covered in this paper, there are yet non-implemented possibilities that can be taken up as a part of the future scope that could be studied on for finer modifications and implementation.

The main idea was the creation of a mechanism where the system of the colour identification would be auto-connected to the continuous flow assembly line, along with the requisites of the assembly of each and every skate/product, which could be the MES interface. This would help not only in the identification of which colour of the wheel has to be mounted to the truck, but also help in the demonstration of the capability of the progress towards the formation of a digital twin.

Now the current state of the capability of the system is not evolved to a state where it can send a signal for a faulty colour being assembled to the skate or even in case of a colour combination that is not required for a particular skate could be stopped from passing to the next phase of the assembly line. Thus, although the current system of the Poka-Yoke is visual, with the help of computational vision and a requesting interface, more automation can be incorporated into the system through this kind of synchronization.

The next step could be refining the Poka-Yoke system, in which it is self-reliant and also it is exclusive from the operator requiring any input. Also, it would display the error location, with an alert light established at this station. And all of this could be linked through the MES and MVISIA system, thus making the Poka-Yoke full proof and automated.

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