A Component-based Design Approach for Energy Flexibility Management in Cyber-physical Systems

by

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“Every good and perfect gift is from above, coming down from the Father of the heavenly lights, who does not change like shifting shadows.”

James 1:17

“Πᾶσα δόσις ἀγαθὴ καὶ πᾶν δώρημα τέλειον ἄνωθέν ἐστι καταβαῖνον ἀπὸ τοῦ πατρὸς τῶν φώτων, παρ’ ᾧ οὐκ ἔνι παραλλαγὴ ἢ τροπῆς ἀποσκίασμα.”

ΙΑΚΩΒΟΥ 1:17

" كُلُّ عَطِيَّةٍ صَالِحَةٍ وَكُلُّ مَوْهِبَةٍ تَامَّةٍ هِيَ مِنْ فَوْقُ، نَازِلَةٌ مِنْ عِنْدِ أَبِي الأَنْوَارِ، الَّذِي لَيْسَ عِنْدَهُ تَغْيِيرٌ وَلاَ ظِلُّ دَوَرَانٍ."

يعقوب 1:17

Declaration

This thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. It has been composed by the author and has not been submitted in any previous application for any degree. The work presented (including data generated and data analysis) was carried out by the author. Over the course of PhD research, parts of this thesis have been published by the author and these publication are given in the provided list of publication.

Fadi Assad

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List of Publications

- **Assad, F.**, Konstantinov, S., Ahmad, M. H., Rushforth, E.J. and Harrison, R., 2021. *Utilising Web-based Digital Twin to Promote Assembly Line Sustainability*. In 2021 IEEE 4th International Conference on Industrial Cyber-Physical Systems. https://doi.org/10.1109/ICPS49255.2021.9468209
- Konstantinov, S., **Assad, F.**, Azam, W., Vera, D.A., Ahmad, B. and Harrison, R., 2021. *A Framework for Developing Web-based Digital Twin for Cyber-Physical Production Systems*. In 2021 IEEE 4th International Conference on Industrial Cyber-Physical Systems. https://doi.org/10.1109/ICPS49255.2021.9468227
- **Assad, F.**, Konstantinov, S., Rushforth, E.J., Vera, D.A. and Harrison, R., 2021. *A Literature Survey of Energy Sustainability in Learning Factories*. In 2020 IEEE 18th International Conference on Industrial Informatics (pp. 98-103). IEEE. https://doi.org/10.1109/INDIN45582.2020.9442119
- **Assad, F.**, Konstantinov, S., Rushforth, E.J., Vera, D.A. and Harrison, R., 2021. *Virtual engineering in the support of sustainable assembly systems*. Procedia CIRP, 97, pp.367-372. https://doi.org/10.1016/j.procir.2020.05.252
- **Assad, F.**, Konstantinov, S., Nureldin, H., Waseem, M., Rushforth, E., Ahmad, B. and Harrison, R., 2021. *Maintenance and digital health control in smart manufacturing based on condition monitoring*. Procedia CIRP, 97, pp.142-147. https://doi.org/10.1016/j.procir.2020.05.216
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Abstract

Traditional production and manufacturing systems are aimed at agility and responsiveness to customer demands. However, sustainability has become a new target that now accompanies the high productivity and quality goals required by manufacturing companies. To this end, energy flexibility emerges as a viable solution that attempts to satisfy all these requirements by the best management of the available energy resources including renewable energies in the context of manufacturing needs.

Following Industry 4.0 revolution, manufacturing processes and systems are being reshaped taking advantage of the advancements in information and communication technologies. Therefore, reaching the manufacturing system's targets of sustainability and productivity takes new means of implementation. As smart manufacturing environments produce remarkable amounts of data, harnessing the resultant data has a significant impact on these targets.

A vital goal of this work is to contribute a new method of managing energy flexibility in digital manufacturing. Unlike the research reported in recent literature, low-level component control is the point of focus. This stems from manufacturing systems' design vision by embedding energy flexibility in the component design. On the way to accomplish this, the theoretical foundation of energy flexibility, manufacturing flexibility and reconfigurability are explained.

Using virtual engineering as a viable system design tool, a research methodology that guarantees the realisation of energy-flexible components of cyber-physical systems is constructed. A digital twin of the energy-flexible component is developed to proactively embed energy flexibility, and interactively exchange data with the physical counterpart. In addition, external services in terms of using Deep Learning and Particle Swarm Optimisation were connected to the digital twin, and could contribute to real-time decision-making.

Keywords: Energy Flexibility; Digital Manufacturing; Component-based Design; Motion Control; Digital Twin; Energy Management; Cyber-physical systems; Industry 4.0

List of Symbols and Abbreviations

Abbreviations

AAS	Asset Administration Shell
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
BoM	Bill of Materials
BoP	Bill of Processes
CAE	Computer-aided Engineering
CAN	Controller Area Network
CAS	Compressed Air Systems
CBAS	Component-based Automation System
CBDA	Component-based design approach
CM, CMfg	Cloud Manufacturing
CNC	Computer Numerical Control
CPCAS	Cyber-physical Compressed Air Systems
CPPS	Cyber-physical Production Systems
CPS	Cyber-physical Systems
CPU	Central Processing Unit
csv	Comma-Separated Values
DC	Direct Current
DES	Discrete Event Simulation
DM	Digital Manufacturing

DR	Demand side Response
DSM	Demand Side Management
DS	Digital Shadow
DT	Digital Twin
ED	Electrical Drives
EFM	Energy Flexibility Measures
EF	Energy Flexibility
EII	Energy Independency Indicator
EMS	Energy Management System
ERP	Enterprise Resource Planning
ESP	Energy Synchronisation Platform
EtherCAT	Ethernet for Control Automation Technology
EV	Electric Vehicles
FCT	Festo Configuration Tool
FHPP	Festo Handling and Positioning Profile
FMS	Flexible Manufacturing System
FoF	Factory of the Future
GSD	General Station Description
HIL	Hardware-In-The-Loop
HVAC	Heating, Ventilation and Air Conditioning
I4.0	Industry 4.0/ Industrie 4.0
ICT(s)	Information and Communication Technology(s)
IP	Internet Protocol
ISA	International Society of Automation

JSON	JavaScript Object Notation
KPI	Key Performance Indicators
MC	Model Calibration
MES	Manufacturing Execution System
MLR	Multiple Linear Regression
ML	Machine Learning
MOO	Machine-oriented Optimisation
MSO	market-side Optimisation
MV	Model Verification
NC	Numerical Control
OEM	Original Equipment Manufacturer
OPC UA	Open Platform Communications Unified Architecture
OT	Operation Technology
PDA	Production Data Acquisition
PLC	Programmable Logical Controller
PLM	Product Lifecycle Management
PPC	Production Planning and Control
Profinet	Process Field Net
PSO	Particle Swarm Optimisation
RAS	Reconfigurable Assembly Systems
RF	Random Forest
RMS	Reconfigurable Manufacturing Systems
RMT	Reconfigurable Machine Tools
SCADA	Supervisory Control and Data Acquisition

SCM Supply Chain Management Systems

SME Small and Medium-sized Enterprises

SQL Structured Query Language

TBS Technical Building Services

VC Virtual Commissioning

VE Virtual Engineering

VFD Variable Frequency Drives

VP Virtual Prototyping

VRE Variable Renewable Energy

VR Virtual Reality

Symbols

χ Constriction coefficient (PSO)

ϵ Error as a percentage of the original value

A Acceleration

A_{lim} Acceleration limit

A_{max} Maximum acceleration

b, c Friction coefficients

c_1 Particle's personal cognition (PSO)

c_2 Particle's social behaviour (PSO)

CT Cycle time

CT_{lim} Cycle time limit

d Damping coefficient

E Energy or consumed energy value

E_{ex} Experimentally measured energy value

E_{pr}	Predicted energy value
J	Jerk
K	Motor constant
k	Spring constant
m	Mass - Inertia
P	Electrical power
$q(t)$	position profile
R	Electrical resistant
r_1,r_2	Random numbers
S	Position, travelled distance
t	time moment
t_0	the initial moment of motion
t_f	the final moment of motion
T_{acc}	Acceleration rise time
T_{ct}	Cycle time length
T_{dece}	Acceleration fall time
V	Velocity
v	Particle's velocity (PSO)
V_{lim}	Velocity limit
V_{max}	Maximum velocity
w	Inertia term (PSO)
x	Particle's position (PSO)
$xbest$	Particle's personal best (PSO)
$xgbest$	Particle's global best (PSO)

Chapter 1

Introduction

"The last thing that we find in making a book is to know what we must put first!"

— Blaise Pascal

1.1 Background

In its broad context, the term "production" refers to the introduction of new products or services to be consumed. As the human needs are endless, the "production responsiveness" has to be in complete readiness to meet everlasting demands. The production system extends to include subsystems such as the storage system, supply chains, manufacturing system and marketing. Considering that the boundaries with the outer world are the technologies, economic status, humans and ecological environment, the dynamics between the production system and its boundaries are ceaseless. Thus, the responsiveness of the production system is reflected in its subsystems' behaviour planning, components engineering and outcomes planning. The focus point of this research is the manufacturing system and assembly automation system in particular (referred to as automation system in short).

The United Nations Organisation (UN) issued in 2015 an agenda titled "Transforming our world: the 2030 Agenda for Sustainable Development" which determined the Sustainable Development Goals. Among these goals are: "affordable and clean energy" (goal 7) [UN 2015a] and "industry innovation and infrastructure" (goal 9) [UN 2015b]. The former targets to double the improvement of energy efficiency by 2030, and the latter aims to upgrade industries so that they become sustainable in terms of the increased resource-use efficiency and environmentally sound technologies and industrial processes. Looking at the automation system responsiveness (i.e. productivity) and the newly emerged requirements (i.e. sustainability), researchers face previously inherited issues to tackle, and future expected advancements to meet. The complexity arises as the number of interactions with the boundaries increase which yields industrial and scientific challenges.

1.1.1 Industrial facts

According to the U.S Energy Information Administration (EIA) [U.S Energy Information Administration 2017], the industrial sector including manufacturing is responsible for the largest share of the world energy consumption. Additionally, world industrial energy consumption is expected to increase by 18% between 2015 and 2040. The main energy sources are petroleum, coal, natural gas, renewables and nuclear energy. Petroleum and other fossil fuels will persist to be the main energy source until 2040 with an increase in natural gas use and decline in coal use. Renewable energies use will continue to grow and nuclear energy will witness insignificant change. Based on the previous expectations, extra greenhouse gases and CO_2 will be produced and further pollution is caused.

Recent changes in climate signify the threats related to the irresponsible use of resources in general and energy in particular. Internationally, the Paris Agreement [UN 2015c] puts forward the commitment of its parties to maintain the global temperature rise below 2°C. Therefore, governments cannot step aside in such vital issues, but push towards stricter regulations to restrict the excessive use of energy. Furthermore, there is a trending lifestyle that is oriented towards care for the environment as a result of the awareness of resources scarcity, and many companies are adopting the concept of cleaner production to satisfy customer demands [Hojnik et al. 2019]. According to the European Climate Foundation [European Climate Foundation 2013], the United Kingdom has achieved remarkable success in the reduction of carbon emissions and started phasing out the use of coal for power generation with increased reliance on renewables. Such success on the supply side should be followed by improvements on the demand sides such as buildings, transport and industry.

Although the use of renewable energy is becoming a "green solution" for decarbonised power supply, it poses challenges on both the supply and demand sides. On the supply side (the grid), the dynamics, control and automation of the power systems constitute a real challenge due to the volatility and variability of power generation by renewable plants [Sajadi et al. 2018]. On the demand side, it is well known that the production rate responds to the market requirements which are unstable by nature and a function of many variables. As a result, the demand of energy has to be in harmony with its availability. The problem even magnifies with the trend for manufacturing facilities to have their own decentralised energy supply on-site [Unterberger et al. 2017b]. In this manner, a new dimension is added to the problem in addition to the "energy efficiency" that is "energy sufficiency". The aforementioned practical issues go in parallel with technological manufacturing milestones and transformations that have emerged in the recent decades. Thus, their relationship with, and the future implications for on, the manufacturing system have to be investigated.

1.1.2 The scientific context

Customer satisfaction has always been the start point of product or service design. Currently, more customisation and personalisation is requested and further involvement of the customer in product shaping and functional description is achievable [ElMaraghy & ElMaraghy 2014]. In the same vein, it has been reported that customer's behaviour is changing from price-sensitive to carbon emission sensitive, [Jiang & Chen 2016], with a willingness for customers to pay more for low carbon footprint products [Bansal & Gangopadhyay 2003], which urges firms to adopt emissions-careful policies. Obviously, these requirements will be reflected in the manufacturing systems and call for organic changes to meet them.

Many manufacturing paradigms were proposed in literature such as biological, holonic, reconfigurable and cloud manufacturing systems [Tran et al. 2019]. A key manufacturing paradigm is the Reconfigurable Manufacturing System (RMS), introduced by the University of Michigan in 1995 [Koren & Shpitalni 2010]. RMS, which proceeded mass, lean and flexible paradigms targets mainly better responsiveness (Figure 1.1). Under the RMS paradigm, the arrangements of system components such as sensors, controllers, algorithms, machines, etc. may be modified as a result of product changes [Mehrabi et al. 2000]. A major shift in the manufacturing capability cannot be made without supportive technological advancements. In the RMS case, the introduction of reconfigurable hardware like modular machine tools, and reconfigurable software like the open architecture controllers have contributed significantly to the realisation of RMS architectures and production goals [Koren 2006]. It should be noted that subcategories exist under RMS that are Reconfigurable Assembly Systems (RAS), and Reconfigurable Machine Tools (RMT).

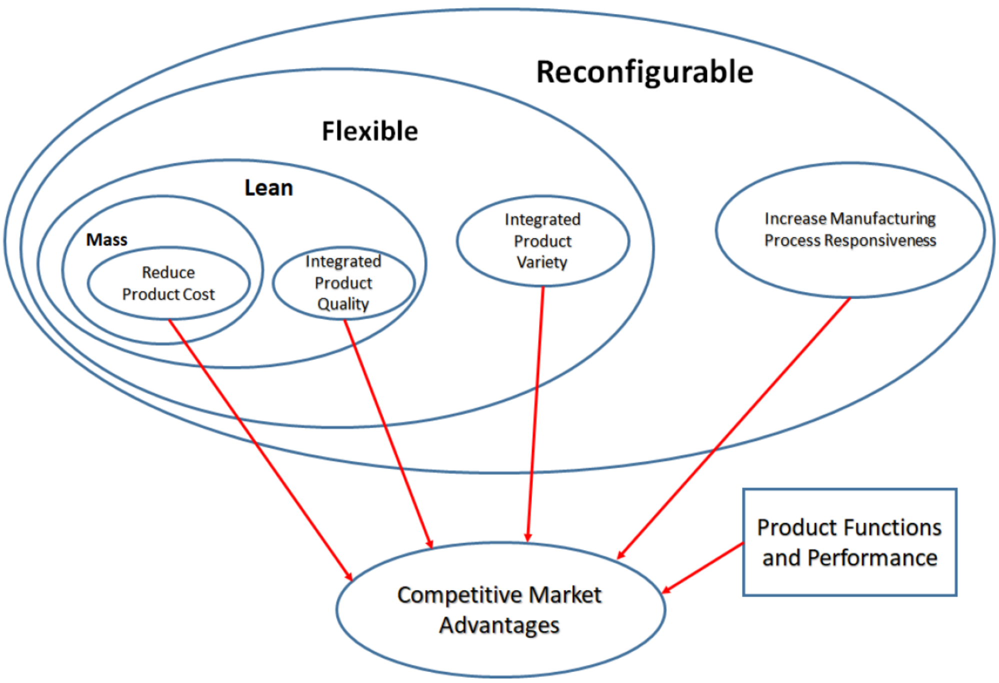


Fig. 1.1: *Economic goals for various manufacturing systems [Mehrabi et al. 2000]*

The recent developments in the Information and Communication Technologies (ICT) have enabled the ongoing “Industry 4.0” revolution, following the third industrial revolution, or digital revolution, where electronics and IT were used to achieve further automation of manufacturing. A distinctive feature of Industry 4.0 is the integration of Digitalisation of Physical Assets/Things, Cloud and Edge Technologies, Internet-of-Things, Internet-of-Services that makes the system a Cyber-Physical System (CPS), where global networks relate the equipment, humans, and supply chains to each other [Shimizu 2016]. As a result, the architecture of the manufacturing system is changed from the classic one to a moderncomplex architecture with a combination of mechatronic-, communication-, information-, control- and automation architectures that employ advanced data and information acquisition, data and information processing from its component, processes and system (Figure 1.2), considering the increased and extended availability and accessibility of data and information.

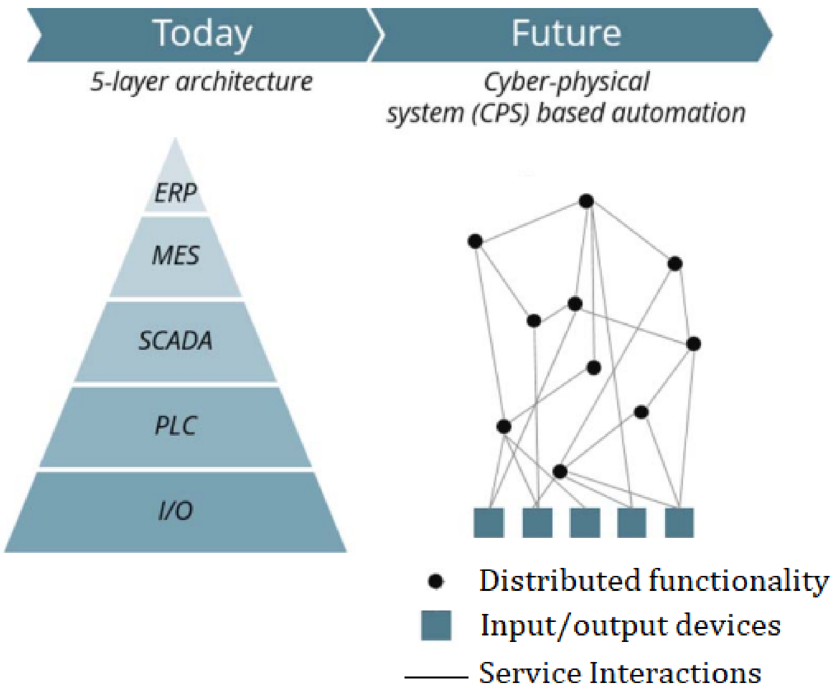


Fig. 1.2: *Future distributed CPS functionality [Harrison et al. 2016]*

As the environmental concerns grow, energy prices get higher, and resource shortages become clearer. Manufacturing systems have to adapt to the new realities, making use of all possible means to address sustainability. To achieve such an aim, Thiede [2012] confirms that sustainable manufacturing (SM) is a must, and manufacturing system need to contribute effectively to the economical, societal and environmental dimensions of sustainability.

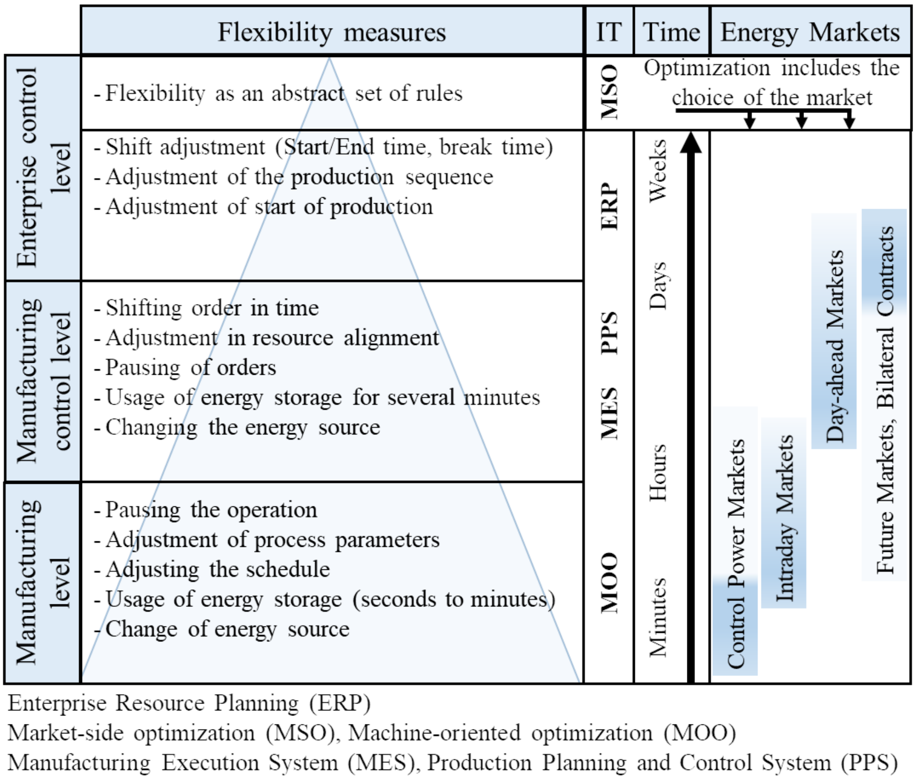


Fig. 1.3: *Allocation of power markets to corporate levels [Seitz et al. 2019]*

Adapting to the available resources, and in harmony with the structure of manufacturing systems (or the automation pyramid), production planning across the levels of the hierarchy should exhibit an energy-flexible behaviour, and respond within different time windows as shown in Figure 1.3. The envisioned view is that at the lower-level automation, machinery-specific restrictions apply, whereas, for the higher-level, logistics-related constraints have to be considered [Seitz et al. 2019]. It can be noted that this view does not regard the changes in the automation pyramid and the shift to digital technologies.

1.1.3 Summary

Driven by resource limitations, expensive energy provision, environmental legislation, international commitment to GHG emissions and CO_2 footprint reduction, the escalating trend to invest in renewable energies and the public interest in environment friendly products, manufacturing systems have to benefit from the most recent technological advancements to rise to these challenges.

On the other hand, for companies to stay competitive in an ever-growing market and with more customised products, manufacturing paradigms are in a progressive development to respond quickly to these variables. Traditional systems aimed at cost reduction and quality improvement, but in the current era, a new aim is imposed which is sustainability. Sustainable Manufacturing as a concept that covers all manufacturing stages is getting more popular. From this perspective, manufacturing paradigms, whether conventional or emerging, should comply with sustainable manufacturing demands by exploiting the up-to-date available technologies.

Industry 4.0 technologies (e.g. Internet of Things and Cloud) transfer industry to the digitalisation era characterised by ubiquitous sensing, data abundance, increased transparency to the system processes and great processing capabilities. Manufacturing systems are being reshaped as Industry 4.0 enabling technologies are becoming cheaper and more obtainable regardless of company size.

1.2 Problem formulation

1.2.1 Vision

Given the new opportunities allowed by Industry 4.0, resources management including materials and energy can be further enhanced. For energy specifically, more accessibility to the process and component operational parameters is guaranteed with the ability to obtain analytics and performance indicators.

The cornerstone in the establishment of “sustainable design” is the automation/manufacturing component (discussed later in 3.1), referred to as component, for short, in this work. Components are here “assets” or “Things” in Industry 4.0 terms. Once the behaviour of the component (the asset) is modelled in terms of its energy consumption, it can be optimised to get the best energy saving or the best use of the available energy. Next, the components in their optimised form serve as the building blocks of the process/machine (or the higher level in the hierarchy). Here, a second optimisation procedure can take place aiming at productivity-sustainability balancing. Further optimisation and performance assessment can be implemented at the higher levels for the same purpose. In principle, the aforementioned procedure is achievable in the traditional manufacturing system design, however, research investigating Industry 4.0 enablers to facilitate design-for-sustainability is still limited.

The work introduced in this thesis is a part of the Automation Systems main research whose aim is the support of the industrial automation systems life cycle, including the design and real-time execution phases. As Industry 4.0 enables the creation of information and data driven systems, it becomes convenient to include sustainability in the design objectives, and to support its foundation with new key tools, e.g., condition monitoring and energy consumption optimisation tools. The current work contributes to the recent research work produced in Automation Systems Group that focuses on:

- System complexity analysis using virtual engineering (e.g. Alkan & Harrison [2019]).
- Sustainable manufacturing in terms of energy consumption based on virtual engineering (e.g. Assad et al. [2019; 2021]).
- Virtual commissioning and code generation (e.g. Konstantinov et al. [2017]).
- Reconfigurable knowledge-driven manufacturing (e.g. Ahmad et al. [2018]).

1.2.2 Problem synthesis

The focus of this study is on discrete manufacturing and automated assembly systems in particular. In such a system, a component consists of the automation device, its own computing hardware and control software [Lee et al. 2004]. Industry 4.0 continues to rely on its “I4.0 component” that is characterised by its ability to save information and has connectivity that allows data transfer. The first step is to get I4.0 component, i.e, to digitalise the Asset/Thing. Then, to analyse energy consumption by understanding the component’s behaviour. In the traditional design approach, this is only achievable after the physical build. However, virtualisation is now extended to the component and process representations. Thus, it is possible to model the component’s energy consumption behaviour, identify the parameters that influence energy consumption and configure the component to reduce energy consumption. In the same vein, it is possible to have energy models in the form of reusable units so that they are transferred between the different manufacturing levels, they should be converted to virtual models.

The concept of energy flexibility (EF) is getting more important with the increased reliance on renewable energy resources. In production systems, it is defined as “the capability to react quickly and cost-efficiently to alternating energy availability” [Popp et al. 2017, Graßl et al. 2014]. On the organisational level, energy flexibility can be understood as the ability to schedule manufacturing processes depending on the energy features [Popp et al. 2017]. Technically on the component level, the prioritising of energy availability in real-time adaption of the energy demand can be expressed in terms of its energy flexibility [Popp et al. 2017]. Considering the freshness and the necessity of the EF concept, it is important to enhance its implementation by means of using the models of both the process and the component to test the manufacturing system’s capability of being energy-flexible, then developing the mechanisms of activating and controlling its energy flexibility.

Once energy flexibility is taken into account when designing the virtual representation of the component, cyber-physical energy-flexible systems can be built using the developed models. This proactive design allows the higher levels of planning to use the information provided at the lower levels to respond to energy availability challenges. So far, scientific literature has not provided an approach for designing such types of components. As a result, the current tools used for manufacturing systems development do not devote enough attention to this problem.

1.2.3 Research goal and hypothesis

The focal point to be investigated in this work is to build energy consumption behaviour modelling starting from the component level at the design phase. This in turn leads to a better understanding of the "energy dynamics" in the established manufacturing system. The adopted vision is the smart factory equipped with Industry 4.0 technologies, where energy consumption is controlled at the component level, and Industry 4.0 enablers are used to re/configure the process/component parameters. This serves as the foundation of energy flexibility in the assembly automation system. Moreover, these findings can help to improve the available EF-enhanced virtual engineering tools, by including further energy efficiency modules. The hypothesis of this research is:

If the component's energy consumption behaviour is identified, it can be embedded in its virtual model (i.e. introduced into its cyber/digital representation), and its energy consumption can be controlled. Thus, energy flexibility can be achieved in the built cyber-physical manufacturing system.

1.2.4 Research objectives

- **Objective 1:** To shape an understanding of the concept of energy flexibility by analysing its evolution and applications as presented in the literature. Then, to link this with manufacturing systems engineering.
- **Objective 2:** To take advantage of the recent advancement in ICTs that led to I4.0. Thus, employing the new provided capabilities in producing a proactive component design and interactive component behaviour. In technical terms, adopting the up-to-date technologies (e.g. IoT and CPS) to be harnessed for manufacturing system energy flexibility improvement.

- **Objective 3:** To provide a systematic approach of embedding energy flexibility in manufacturing system early design phases. On one hand, to help system builders/developers control component-level energy consumption, hence manage the expected energy consumption and improve the sustainability of processes. On the other hand, to enable decision-making and its possible enforcement mechanisms.

1.2.5 Intended contributions

The intended contributions to the body of ongoing research on sustainable manufacturing under Industry 4.0 are technical, from the component performance optimisation perspective, and systems-engineering related, from the life-cycle perspective.

At the component level, it is aimed to prove that at the design phase, there is a possibility to take advantage of the collected data to identify the most sustainable performance of the component. By establishing a correlation between the operational parameters and the less energy-consuming modes of operation, they can be selected and tuned in the next phases of the life cycle to adapt to the required sustainable manufacturing/ production and energy flexibility requirements.

At the system engineering level, when energy flexibility is targeted, Industry 4.0 developed components are realised as building blocks. Those building blocks are of identified behaviour and visible parameters, thanks to the IoT technology and data storage in the developed virtual model. As a result, building a cyber-physical sustainable system is feasible where the virtual counterpart deploys artificial intelligence and decision-making algorithms that process the digitalised data and information contained in the cyber-physical component.

1.3 Dissertation outline

To deliver the outlined research objectives, the dissertation is structured as follows:

- **Chapter 2** reviews the concept of flexibility of both manufacturing and energy.

The definitions and fundamental concepts related to Industry 4.0, sustainability and energy flexibility within this work's context are also included.

- **Chapter 3** reviews the literature on component-based design. Energy management under Industry 4.0 and the different approaches of energy flexibility are then classified and discussed in order to identify research gaps. An explanation of electric drives' energy consumption is included, as it will be studied as a manufacturing component.
- **Chapter 4** presents the suggested research methodology where research questions are identified and the type of analysis necessary to achieve research objectives are provided.
- **Chapter 5** explains trajectory design principles and its related energy consumption. The possible ways of achieving energy flexibility for this application are then put forward.
- **Chapter 6** demonstrates a vision of supporting manufacturing system sustainability across the life cycle. Next, a methodology for embedding energy flexibility in the component virtual model is introduced by means of virtual engineering supported by IoT.
- **Chapter 7** demonstrates the application of the proposed methodology experimentally in three phases: prediction of energy consumption, building the digital twin, and connectivity to external functionalities.
- **Chapter 8** summarises the accomplished work along with research contributions, benefits and an outlook to future work.

Chapter summary

This chapter has introduced the recent facts about manufacturing energy sustainability and identified the motivation for doing this research. The morphology, anatomy, research hypothesis and goals of this work were also briefly introduced.

Chapter 2

The Flexibility of Manufacturing and Energy

"There are two types of mind ... the mathematical, and what might be called the intuitive. The former arrives at its views slowly, but they are firm and rigid; the latter is endowed with greater flexibility and applies itself simultaneously to the diverse lovable parts of that which it loves. "

— **Blaise Pascal**

THE purpose of this chapter is to provide a background on the topic of focus in this dissertation. Light is shed on the concept of "flexibility" in Reconfigurable Manufacturing Systems (RMS) and Industry 4.0. Then a background to energy flexibility in manufacturing systems is given in order to show the elements inherited from RMS. Additionally, the terminology to be used later in the body of this dissertation in relation to energy flexibility and Industry 4.0 is defined.

2.1 Flexibility in manufacturing

2.1.1 Concept

Flexibility, as a term, has several meanings. In mechanical and structural engineering, flexibility is linked to elasticity and stiffness. Young modulus expresses the material's elasticity, and based on the structure's shape parameters (e.g. length, diameter, ... etc.), the stiffness is calculated. Thus, flexibility is the opposite of stiffness, .i.e., the more flexible an object is, the less stiff it is [Wikipedia 2019]. Starting from this basic understanding, Chryssolouris [1996] refers to an analogy between the manufacturing and mechanical systems (Figure 2.1). In this vision, the measure of the system flexibility is ζ, and the transfer function describes the manufacturing system's response to the change of demand.

$$\zeta = \frac{1}{2}\sqrt{\frac{c^2}{km}}$$

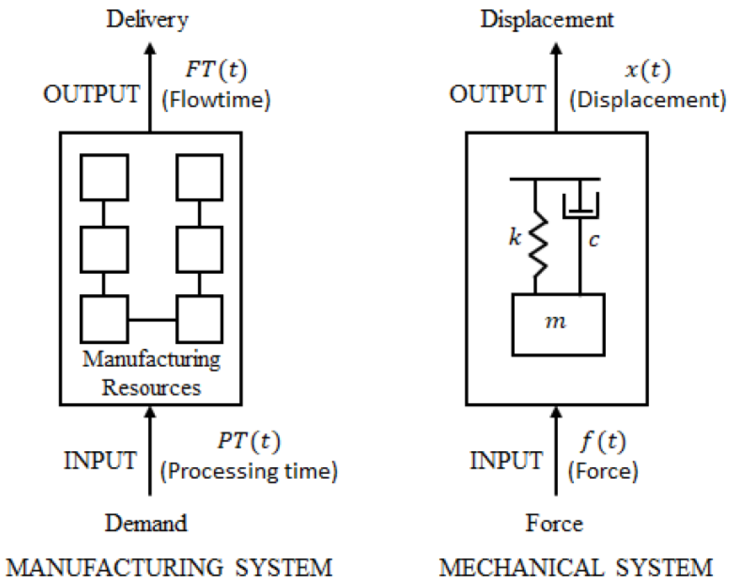


Fig. 2.1: *Analogy between a manufacturing and a mechanical system [Chryssolouris 1996]*

2.1.2 Flexibility under Reconfigurable Manufacturing Systems (RMS)

The concept of Reconfigurable Manufacturing Systems (RMS) was proposed by the University of Michigan in 1995 [Koren & Shpitalni 2010]. An ideal RMS should have reconfigurable software and reconfigurable hardware with both having the abilities of convertibility, diagnosability and scalability [Dashchenko 2006]. RMS characteristics are shown in Table 2.1. Material handling systems, mechanisms, modules and sensor, as well as process plans and system control algorithms, can be good examples of the reconfigurable components [ElMaraghy 2008].

Characteristic	**Definition**
Modularity (components are modular)	The modular design of both the software and hardware
Integrability (interfaces for rapid integration)	System and components should be designed for ready *integration*
Convertibility (design for functionality changes)	System's adaptability to new products and fast switching between current products
Scalability (design for easy diagnostics)	Easy modification of production capacity by adding or removing manufacturing resources and/or changing the system's components
Diagnosability (design for easy diagnostics)	Fast detection of quality and reliability root causes
Customisation (flexibility limited to part family)	Matching the application with the system's capability and flexibility

Table 2.1: *Key characteristics of a reconfigurable manufacturing system [Mehrabi et al. 2000, Koren & Shpitalni 2010, Koren & Ulsoy 2002]*

In the context of RMS, flexibility is originally regarded as a characteristic of the RMS that allows the production of various products, and even the system itself [Mehrabi et al. 2000]. Therefore, the Flexible Manufacturing System (FMS) is defined as an integrated system of manufacturing machine modules and material handling equipment under computer control for the automatic random processing of palletised parts [ElMaraghy 2005], where a flexible manufacturing system does not need to be reconfigurable, however, a Reconfigurable Manufacturing System contributes to flexibility.

Although the previous definition of FMS is inspired by machine tools, it is not exclusive to machine tools or palletised parts. Moreover, putting customised flexibility into action is significantly important for improving productivity [Koren & Shpitalni 2010]. In practice, the following types of flexibility can be observed [Chryssolouris 2005, Wiendahl et al. 2007]:

- Product flexibility: producing many part types using the same equipment.
- Operation flexibility: producing a group of products by means of various materials, machines, operations and their sequence.

- Capacity flexibility: the system's ability to control the production volume of different products to respond to the market demand while keeping profitability.

It should be noted that other types of flexibility exist such as machine flexibility, material flow flexibility, etc.

To compare flexibility and reconfigurability, traditional flexibility is understood as the ability of a system to change its behaviour without changing its configuration, whereas reconfigurability is the ability to change the system's behaviour by changing its structural configuration [Wiendahl et al. 2007]. Depending on the production level and product level (e.g. workpiece, sub-product) of concern, the term flexibility can differ. Therefore, Wiendahl et al. [2007] advise to use the term "changeability" as it is more inclusive. As a conclusion, changeability can be interpreted as flexibility or reconfigurability based on the system boundaries. It should be noted as "changeability" did not become a popular term compared to "flexibility".

Interestingly, the theoretical foundation of RMS does not regard sustainability in any of its intended design principles. However, Bi [2011] believes that RMS as a manufacturing paradigm can contribute to sustainability in relation to the used materials, used tools, waste and energy. Also looking at the big picture, sustainability domain, in all its dimensions (social, economic and environmental), can have goals which have to be translated into reconfiguration measures in the changeability domain [Azab et al. 2013]. In addition to the RMS characteristics in Table 2.1, Singh et al. [2017] unexpectedly add "sustainability" as an RMS characteristic, where 'reconfigurability' can be a facilitator to achieve sustainability.

2.1.3 Flexibility and sustainability under Industry 4.0

2.1.3.1 Overview of Industry 4.0

Industry 4.0 (or Industrie 4.0 in German, I4.0 for short) was launched in 2011 by the German Federal Government, then announced as their strategic initiative in 2013 [Xu et al. 2018]. Historically, I4.0 is the movement from Industry 3.0, characterised by numeric control and automation, to digital manufacturing. Such a change has been attributed to the Internet of Things (IoT) that enabled machine-to-machine (M2M) communication, the autonomy (machine's ability to self-behave) and Cyber Physical Systems (CPS) [Oztemel & Gursev 2020]. The use of I4.0 technologies is expected to make manufacturing facilities "smart" in terms of enabling them to produce customised products and improving their operational flexibility and efficiency [Petrillo et al. 2018]. Therefore, with its introduction, I4.0 and its enablers are believed to increase flexibility in manufacturing and production [Zhong et al. 2017].

When speaking about I4.0, three types of integration are recognised [Liao et al. 2017]: (1) *Horizontal integration* which takes place between different IT systems in different stages of manufacturing within a company (e.g., in production and, logistics) or across several companies (e.g., in value networks) (2) *Vertical integration* which takes place between different OT and IT systems at different hierarchical levels in manufacturing (e.g., sensor and actuator, MES, ERP, ...) (3) *End-to-End digital integration*: which is the engineering process of integrating both the real and digital worlds across the product's entire value chain and including companies and customer requirements.

2.1.3.2 Industry 4.0-related definitions

I4.0 is an evolving domain, in which the terminology and its related definitions are also maturing. There are a number of similar definitions, but with subtle differences, which could stem from different disciplines or use cases. With this reservation, the following paragraphs provide some of the more established, relevant, definitions.

Cyber-Physical Systems (CPS): are systems of collaborating computational entities which are in intensive connection with the surrounding physical world and its on-going processes, providing and using, at the same time, data-accessing and data-processing services available on the Internet [Monostori et al. 2016].

Cyber-Physical Systems Production Systems (CPPS): "a special term that depicts the introduction of the concept of CPS in the production domain in order to make production processes in general or production systems in particular smarter" [Gerhard

2017].

Industrial Cyber-Physical Systems (ICPS): "systems that have the label of CPS and more precisely their applicability in the industrial domain" [Leitão et al. 2016].

Internet of Things (IoT): a 'thing' in this term denotes the same concept as a physical 'entity' [Industrial Internet Consortium 2018a]. An 'entity' is an item that has recognizably distinct existence [Industrial Internet Consortium 2018b]. IoT becomes "the network of physical objects, devices, vehicles, buildings and other items embedded with electronics, software, sensors, actuators and network connectivity that enables these various objects to collect and exchange data" [Plattform Industrie 4.0 2020].

Industrial Internet of Things (IIoT):"system that connects and integrates industrial control systems with enterprise systems, business processes and analytics [Industrial Internet Consortium 2018b].

Big Data: "massive data sets and stream computing that due to their large size and complexity are beyond the capabilities of traditional databases and software techniques" [Camarinha-Matos & Afsarmanesh 2014].

Digital Twin (DT): "Information that represents attributes and behaviours of an entity". In other words, "a formal digital representation of an entity, with attributes and optionally computational, geometrical, visualisation and other models, offering a service interface for interacting with it, adequate for communication, storage, interpretation, process and analysis of data pertaining to the entity in order to monitor and predict its states and behaviours within a certain context" [Boss et al. 2020].

Digital Manufacturing (DM): "A set of tools used for information management that assists decision-making throughout the manufacturing life cycle. Based on computer integrated systems, simulation, information-sharing models and collaboration tools to design, redesign and analyse the factory, the product and the manufacturing process in an integrated way" [da Silva et al. 2019].

2.1.4 The impact of Industry 4.0 on flexibility

It is agreed in academic literature and industrial practice that I4.0 offers the potential to revolutionise manufacturing systems' design in all aspects. The multi-directional integration explained earlier is leading to a change in the boundaries of the manufacturing system's components. As a result, the reconfigurability and flexibility of the system are changing. Possible domains of this are system development, diagnostics and maintenance, in addition to the operation of automated systems [Jazdi 2014].

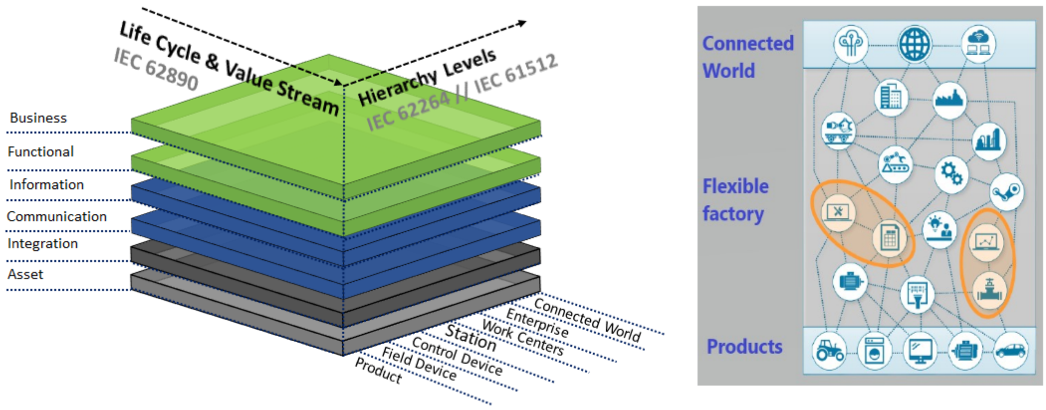


Fig. 2.2: *Reference Architectural Model Industrie 4.0 (RAMI 4.0) [Plattform Industrie 4.0 2018]*

Figure 2.2 shows the Reference Architectural Model Industrie 4.0 (RAMI 4.0). In this model, embedding flexibility in systems and machines takes place by distributing functions through the network where machines manage the production autonomously in an efficient, flexible and resource saving manner [Plattform Industrie 4.0 2018]. In order for modern systems to exhibit the required flexibility, reconfigurability and intelligence, they should possess autonomous control system [Boccella et al. 2020]. Reaching a high degree of autonomy, like in a self-organising factory, can be done by using digital twins and data-driven production operations [Lu et al. 2020].

I4.0 yielded "smart manufacturing" that is utilised in "smart factories". Flexibility is regarded as one of the main characteristics of a smart factory which has to correspond to the ecological requirements by means of intelligent production processes and self-configuration [Shrouf et al. 2014a]. IIoT - which is the backbone of I4.0 - promises more efficient value creation and increased flexibility in addition to the customisation of products and services [Kiel et al. 2017]. Thus, the highest priorities for companies to create value are flexibility and sustainability [Demartini 2017]. Against this background, "energy flexibility" is understood as an additional type of flexibility that is enabled by the use of Industry 4.0 technologies. Furthermore, the design required to achieve energy flexibility is inspired by RAMI 4.0 starting from the "Asset" and moving across the "Layers" axis.

Despite the great flexibility granted by I4.0, it can limit production/manufacturing systems' modelling, thereby, identifying their availability and productivity [Long et al. 2017], which means a poor possibility of estimating the system's future performance.

It should be noted that similar to Industrie 4.0 initiated in Germany, there are similar manufacturing digitalisation initiatives that were launched in other countries such as "Industrial Internet Consortium" (USA), "Made in China 2025" (China), "High Value Manufacturing Catapult" (UK), "Usine du Futur" (France), "Fabbrica del Futuro" and " Fabbrica Intelligente"(Italy), "Smart Factory" (Netherlands), "Produktion 2030" (Sweden), "Produktion der Zukunft" (Austria) [MAPI Foundation 2015, European Parlimant 2016].

As the terminology related to Industry 4.0 is explained, and the possible meaning of 'flexibility' is clearer, it is necessary explain the flexibility of energy.

2.2 Energy flexibility in manufacturing

2.2.1 Sustainability, sustainable manufacturing and energy sustainability concepts

Sustainability has three dimensions: economic, social and environmental. Some metrics of sustainability in each case are [Lu et al. 2011]:

- *Economy*: e.g. cost, investment, product quality, profitability and innovation.
- *Environment*: e.g. efficient use of water, efficient use of material, end-of-life

management, residues and energy consumption and its efficiency.

- *Society*: e.g. education, health and safety, customer satisfaction and societal well-being.

Increasing energy sustainability in manufacturing continues to evolve as manufacturing systems evolve to respond to customer's needs. According to the US Department of Commerce (2015), Sustainable Manufacturing is "the creation of manufactured products that use processes that minimise negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound" [Bi 2011]. From companies' perspective, a "green product" is the product that was manufactured with the least consumption of energy, and based on this concept, the European Commission prioritises research on having more energy efficient production processes and the control of energy consumption [Garetti & Taisch 2012]. Thus, as manufacturing systems are built to make profit, the targeted productivity can never be ignored when planning a system's sustainability. Besides, from cost perspective, there should be some measures to indicate energy sustainability performance. To quantify energy sustainability in manufacturing, the concepts below are typically found in literature:

- **Energy efficiency** is usually linked to the amount of the energy consumed per unit or product [Thiede 2012].
- **Energy effectiveness** can be expressed as the time used up per resource to manufacture the product [Pach et al. 2014].
- **Energy awareness** can be seen as more inclusive as it accounts energy data as a stakeholder in the production management aiming at decreasing waste and cost [Shrouf et al. 2014a].
- **Energy management in manufacturing** is based on measurement, key performance indicators (KPIs), monitoring and evaluation and control [May et al. 2017].

Manufacturing system life cycle and product life cycle go in parallel and influence each other. Therefore, energy sustainability-related aspects can be influenced by the changes in both life cycles. These facts constitute the foundation that yields manufacturing energy flexibility as its target is achieving sustainability without sacrificing the intended level of productivity. In the following sections, this development is investigated.

2.2.2 *History and concept development*

The concept of energy flexibility stems from the economic pressure due to the fluctuations of energy prices. Back in 2004, Elliott [2004] proposed the fact that the volatility in the energy prices should be handled by switching fuels, varying loads and shaving peaks demand. Another good justification of adopting the concept of energy flexibility is the increased popularity of variable renewable energy (VRE) like wind and solar resources, and energy generation on-site to be consumed by the manufacturing facility [Beier et al. 2015].

Generally, the field of building energy management is more advanced when it comes to energy consumption management. The sector of energy management in buildings witnesses the development in the concept and application of the energy flexibility. For example, Madsen [2012] suggested the utilisation of the heating systems and hot water tanks in the ordinary houses (consumer side) to store energy, .i.e., recognising consumers' behaviour and giving them an economic incentive to consume energy at the right time.

Modern manufacturing targets have changed from the triangle made of quality, cost and time to the pyramid made of sustainability, time, quality, cost and flexibility with sustainability being at the top and the rest across the base [Schulz et al. 2018]. Pierri et al. [2020] state that energy flexibility is not required by customer, therefore, it is not product related. Nevertheless, Simon et al. [2017] attribute the need for energy flexibility to the changes in the energy markets, which require the manufacturing system to adapt to them.

Scandinavian countries had a very early consciousness of the importance of energy flexibility. One of the first suggestions about energy flexibility was in [Alm et al.

2001] (Norway) in the form of switching steam generating boilers in the pulp and paper industry between different types of fuels such as electricity, oil and biomass. In the same industry, Døhl [2002] introduces the idea of energy flexibility via production control: either producing an output that is a combination of less energy-consuming products, or adopting a less energy-intensive production technology. For this reason, a cost function is developed to solve the optimisation problem. This study is a pioneer study as it could address energy flexibility in an industry that is a mixture of chemical and mechanical pulping. Currently, Scandinavian countries still give this topic a lot of attention but in the field of buildings' energy flexibility rather than in manufacturing. However, German research institutions have received considerable funding to research manufacturing energy flexibility as Germany phased out nuclear stations in 2011 [Schultz et al. 2015][1]. After that, the goal in Germany was to generate 80% of the energy consumed in industry through renewable resources, which typically suffer from a greater volatility in supply. Therefore, it was proposed to have energy flexibility as a design variable [Unterberger et al. 2017a].

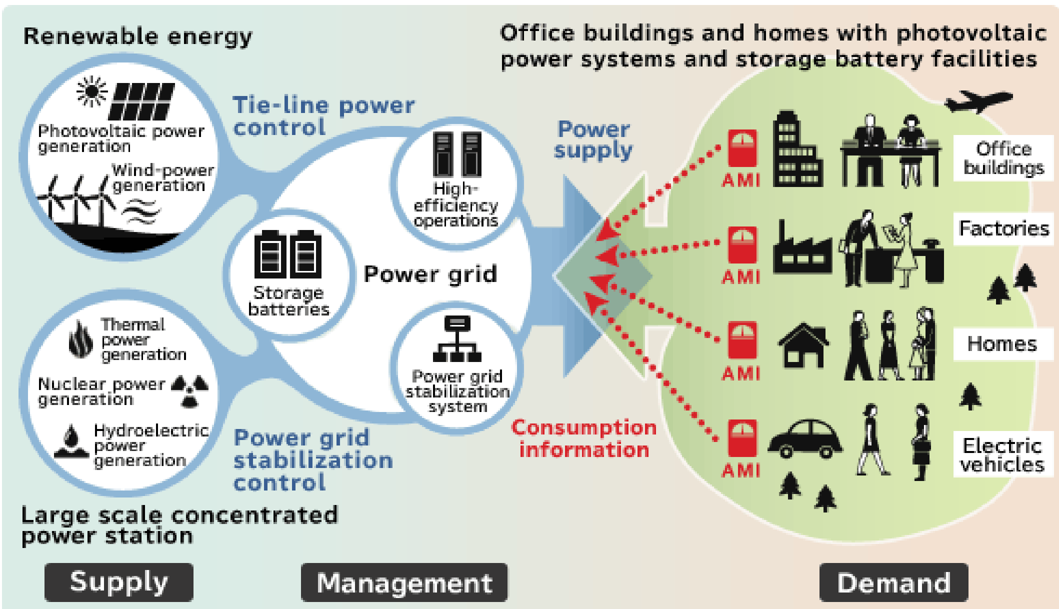


Fig. 2.3: *The parties involved in energy consumption and generation [Hitachi 2010]*

Looking at Figure 2.3, we can see three clear divisions: the supply, the

[1] 1 An example is Green Factory Bavaria: http://greenfactorybavaria.de

management and the demand. Consequently, three types of flexibility will exist: supply flexibility, grid flexibility and consumption flexibility. These three types of flexibility are subjects of active research, especially with the wide spread of smart technologies.

On the supply side, the term power flexibility is more commonly used, in relation to varying the generation methods or the generation technology.

2.2.3 Related definitions

In the following, some terms used in energy flexibility study are defined as they will be used later in the body of this dissertation.

Demand Side Management (DSM): "(DSM) refers to technologies, actions and programmes on the demand-side of energy metres that seek to manage or decrease energy consumption, in order to reduce total energy system expenditures or contribute to the achievement of policy objectives such as emissions reduction or balancing supply and demand." [Eissa 2011, Warren 2014].

Demand Side Response (DR): DR includes both modifications of electricity consumption by consumers in response to price and the implementation of more energy efficient technologies [Greening 2010].

For large consumers, demand can be classified into flexible and inflexible loads. A flexible load can be rescheduled according to the electricity cost, whereas an inflexible one does not allow this potential due to the limitations imposed by production processes [Angizeh & Parvania 2019].

In the context of this research, DR is approached in an Industry 4.0 context, where more data are available from manufacturing processes and components, and thus the response is easily understood and quantified. In fact, once DR is identified, electricity suppliers would utilise it for pricing purposes, while manufactures can shift loads based on it. Regarding the relation between DR and DSM, Barbato & Capone [2014] consider DR a reactive solution that aims to change the peak demand and on the short term, whereas DSM is a proactive solution that urges consumers to decrease their energy consumption in the long term. DSM is an umbrella term that includes energy efficiency and DR [Shrouf et al. 2014b].

Despite the fact that manufacturing industry is a major energy consumer, research on implementing DR in industrial facilities is still limited due to the following factors [Huang et al. 2017]:

- Contrary to the residential or commercial energy consumption, assessing industrial processes consumption needs to take into account a variety of resources (e.g., raw and intermediate material).
- Industrial facilities show a great diversity and complexity. Therefore, creating a generalised model is not a straightforward process.
- Few efficient energy management schemes for real-time-based DR exist.

Prosumers, prosumager: A prosumer retrieves both energy from the grid and self-produced energy from rooftop solar panels or other generating devices, while injecting into the grid the power in excess of its need. A prosumager owns a storage facility, too, that allows it to create more value from its self-generated energy and consumption behaviour [Stagnaro & Benedettini 2020].

Technical Building Services (TBS): They are responsible for essential tasks like heating and cooling (including space and process heat); ventilation and air conditioning; power engineering (e.g. lighting) and water/media supply and treatment [Thiede 2012].

2.2.4 Measures of energy flexibility

EF Measures are defined as the "conscious and quantifiable actions to carry out a defined change of operative state in an industrial system" [Tristán et al. 2020]. The research in EF in manufacturing according to different measures [Beier et al. 2017] such as the planning horizon (strategic, tactical, operational), execution (e.g., in real-time), application vision (single-stage, multistage). Similar time-base measures are introduced in Keller et al. [2016a]. One classification of EF is based on the measures used for conducting it, which are introduced in Table 2.2 for illustration.

Theme	Action	Reference
Process	Adaptation of process starts	Simon et al. [2018], Graßl & Reinhart [2014]
	Process parameters	Rackow et al. [2015]
	Processes' interruption	Rackow et al. [2015]
Machine	Adaptation of machine scheduling	Simon et al. [2018], Graßl & Reinhart [2014]
	Machine utilization adjustment	Rackow et al. [2015]
	Avoiding parallel start-ups of high-energy demand machines	Popp & Zaeh [2014]
Order	Adaptation of order sequence	Simon et al. [2018], Graßl & Reinhart [2014]
Staff	Adaptation of staff free time	Simon et al. [2018], Graßl & Reinhart [2014]
Shift	Adaptation of shift times	Simon et al. [2018], Graßl & Reinhart [2014]
Product	Product specific plant loading	Unterberger et al. [2017a]
	Product specific process parameters	Unterberger et al. [2017a]
Job	Job's start shifting	Rackow et al. [2015]
	Job's order rearrangement	Rackow et al. [2015]
Maintenance	shifting maintenance period	Rackow et al. [2015]
Production	shifting of production time slots	Rackow et al. [2015]
	Switching production sectors on or off	Unterberger et al. [2017a]

Table 2.2: *Energy flexibility measures (EFM) [Simon et al. 2018, Graßl & Reinhart 2014, Rackow et al. 2015, Unterberger et al. 2017a]*

The general idea is to have the production cost per unit reduced after energy flexible adjustment is applied [Rackow et al. 2015]. For TBS specifically, these measures are: multivariance (using more than one source for energy feed), energy tolerance in demand for useful energy [Flum et al. 2018].

2.2.5 *Design principles*

Evaluating the energy flexibility of a manufacturing process depends on two criteria: the consumed power and the time window within which this power is consumed [Lombardi et al. 2019]. Unterberger et al. [2018] specified eight design principles of energy flexibility based on the characteristics of changeable systems. These principles are:

- *Modularity*: The ability of having multiple system states by equipping the system with units/elements' variety.
- *Availability*: Being able to react to environment changes at any time.
- *Scalability*: The possibility of combining, substituting or eliminating the stations in order to have new configurations.

- *Predictability*: Defining the energetic behaviour when transferring into a new state.
- *Connectivity*: The obtainment of material, energy and information flows.
- *Energy efficiency*: Increasing the flexibility measures' duration and reducing the wasted energy.
- *Self-regulation*: Less effort for making system changes by using decentralised control.
- *Cost reduction*: Decreasing flexibility cost can increase flexibility potential.

Chapter summary

The development of the flexibility concept has been explored in manufacturing generally, in Reconfigurable Manufacturing Systems and in Industry 4.0. In order to understand the impact of Industry 4.0 on flexibility, some definitions and concepts related to Industry 4.0 are presented.

On the sustainability side, the foundation of energy flexibility in manufacturing and its related terminology are introduced. Then, the measures of energy flexibility, its proposed design principles, its expected risks and its feasibility are highlighted.

Chapter 3

Literature Review

"Il n'est pas certain que tout soit incertain

It is not certain that everything is uncertain"

— **Blaise Pascal**

THe following literature review will be divided into three main streams: energy management under I4.0, energy flexibility in manufacturing, and motion control utilisation for increasing sustainability.

3.1 Drivers for component-based design

Automation Systems Group (ASG) at WMG - the University of Warwick and previously Manufacturing Systems Integration (MSI) group at Loughborough University have a long record in promoting and supporting component-based design methods for automation systems.

A component is "an autonomous unit consisting of the automation device (i.e. actuator, sensor) with its own computing hardware (processor, memory, communication interface electronic interface to the automation device) and control software (application programs, operating system and communication protocol)" [Lee et al. 2004]. Alkan & Harrison [2019] define component-based automation system (CBAD) as a "constellation of basic components which can be represented in various design domains, such as: mechanical, electrical, pneumatic, control, etc.". From the perspective of semantic web services, an "intelligent component" has specialised production skills, reasoning, inference and even learning capabilities that enable decision-making based on the context [Lastra & Delamer 2006]. It can be noted that a "component" is not limited to a certain domain but, most importantly, it can be interfaced with other components, systems etc. In addition, component-based design is understood and interpreted within a manufacturing paradigm and the available technologies.

Model-based design follows the mindset of "correct-by-construction", where the properties of the constructed models of the designed system should predict with acceptable accuracy the properties of the manufactured system [Sztipanovits et al. 2014].

3.1.1 Component-based design in RMS

As RMS are designed to tackle the quickly changing markets, component-based software engineering can potentially provide the tools necessary for building the targeted manufacturing planning and control system [Ismail & ElMaraghy 2009]. This comes as a part of the process of component-oriented development by starting from reusable, self-contained, blocks of code. Also, Vera et al. [2009] denote that using the component-based approach in building machines yielded a great advantage as components' models could be reconfigured and reused when testing multiple scenarios of machine's configurations. Thus, relying on this concept, it is possible to develop tools that support the virtual construction of automation systems by validating the process, defining the control behaviour, commissioning and control system runtime deployment [Ahmad et al. 2013]. Some additional benefits include layout visualisation and production analysis (e.g. related to identifying bottlenecks, and line balancing) [Heilala et al. 2008].

The architecture of a component-based system is considered to be modular by nature, which helps the designer(s) orientate their focus [Du & Yu 2009]. Choosing the modules is similar to picking the desired items from an e-catalogue then ordering them to obtain the targeted flow, system layout and deliverables [Heilala et al. 2008]. Later on, the end-user/ system-integrator configure/reconfigure the system to meet the required customer needs. For control systems specifically, selecting the modules is strongly dependant on the level of granularity to achieve the required module's functionality [Harrison et al. 2006]. Otherwise, choosing the wrong modularity leads to difficulty in building and reconfiguring the system. The added-value is not purely the technical - control dimension, but also encompasses the dimensions of enterprise, supply chain and life cycle [Jain et al. 2010].

The actual environment that supports such development of RMS is simulation either with specialised simulation tools or an integration of simulation capabilities in the industrial automation runtime environment [Hegny & Zoitl 2010]. Deploying the developed models in simulation tools, it becomes possible to test "what if" scenarios of the control logic including its physical, kinematic and dynamic characteristics [Ong et al. 2006] reducing the development time and cost.

It can be concluded that under the umbrella of RMS, component-based design matured and reached great applicability in terms of simulation models which can evolve to virtual models. As a result, the reconfiguration concept, proposed by Koren and theorised in Koren & Ulsoy [2002], turned to be on the software side more than on the hardware, where many simulation tools were developed for this purpose. Besides, the developed technologies and methods did not expire but rather continued to grow. This period is roughly between 1998-2013 which coincides with the introduction of I4.0 accompanied by the advancements in Information and Communication Technologies (ICTs).

3.1.2 *Component-based design in Industry 4.0*

In the design phase of the system life cycle, the components of the system go through multiple configuration/reconfiguration procedures as a result of the changes in product design [Assad et al. 2019]. As a manufacturing paradigm, I4.0 is meant to deal with these changes and rise to the challenge of short product and plant life cycles [Lüder et al. 2017].

To foster productivity in CPS, two main technologies are realised: component-based design and model-based design [Saldivar et al. 2015], where CPS supports the capabilities of virtualisation, interoperability and decentralisation. In a model and component-based design flow, the starting point for building system models is component models with the guidance of architectural specifications that include system scope, content, and composition [Harrison et al. 2016]. Despite the success they proved so far, they still face the following problems [Sztipanovits et al. 2014]:

- Heterogeneity of CPS models including the physical nature and the level of abstraction across the various engineering disciplines.
- Heterogeneity of design tools: as toolchains are discipline-oriented, the integration across their suites is not straightforward and sometimes unsupported.
- Life-cycle heterogeneity: this is faced when integrating the physical part with the design of the manufacturing process that produces it.

Analogous to reconfigurable components in RMS, there are I4.0 components. For every I4.0 component, there is an asset administration shell (AAS) which is a "virtual digital and active representation of an I4.0 Component in an I4.0-System" [Wagner et al. 2017]. I4.0 Component is a "worldwide identifiable participant able to communicate consisting of Asset Administration Shell and Asset including a digital connection" [Wagner et al. 2017]. The AAS has to cover the virtual representation and the object (thing) [Zezulka et al. 2016], and the data of a virtual representation may remain either in the object or in an IT system (higher level) - which actually refers to the aspect of I4.0-compliant communication [Prinz et al. 2019]. In other words, AAS is the logical unit responsible for the virtual representation, the interaction with the system and resource management [Moghaddam et al. 2018]. As a result, the essential characteristic of the I4.0 component is the combination of both physical and virtual worlds with the aim of providing certain functionalities within them [Röpke et al. 2016].

3.2 The relationship between RMS and CPPS

3.2.1 The support of functions

The five levels of CPS architecture are [Lee et al. 2015]: **C**onnection, **C**onversion, **C**yber, **C**ognition and **C**onfiguration. Taking into account that every 'reconfiguration' is setting a new 'configuration', it can be noticed that the final aim of both RMS and CPPS is still the same. However, the increased connectivity, and thus, integration yields more accessibility to the systems' resources. This level can be described as the feedback sent from the cyber space to its physical counterpart acting as supervisory control, where it has the following basic functions [Shin et al. 2018]:

(i) Self-configure for resilience.

(ii) Self-adjust for variation.

(iii) Self-optimise for disturbance.

The reconfiguration procedure covers multiple aspects starting from adaptions in the software domain up to essential changes of the electrical or mechanical system parts [Bauernhansl et al. 2020, Grochowski et al. 2020]. With the aim of reaching the ultra-flexible factory, Bauernhansl et al. [2020] refer to many categories of reconfigurability such as system, software, control, process and machine where they conclude that a CPPS possesses the required capabilities to enable ultra-flexible factories thanks to their information models and intelligence. One component of a 'smart factory' according to Wang et al. [2016a] is "smart objects" that can dynamically reconfigure to achieve further flexibility, and this can be done with the support of big data-based feedback.

RMS characteristic	Industry 4.0 technologies
Modularity	Smart devices, collaborative robotics and standardised interfaces
Integrability	CPS, integrated sensors, wireless communication, cloud manufacturing, IoT
Diagnosability	CPS, the IoT, big data analytics, 3D scanning
Adaptability	Virtual Reality and Augmented Reality
Customisation	All the above

Table 3.1: *Core characteristics of RMS and Industry 4.0 corresponding technologies [Maganha et al. 2020]*

In a study conducted by Ivanov et al. [2020] regarding the state of the art research on I4.0, it turned out that CPS and IoT are of researchers' interest across all disciplines. Nevertheless, those who conduct research in the areas of industrial, mechanical and control engineering stressed the role of RMS. On the other hand, those whose background is related to operations management give more attention to the cloud manufacturing technology. Another study by Maganha et al. [2020] shows, based on the literature resources, that I4.0 technologies support the reconfigurability in the existing manufacturing systems. Table 3.1 summarises those findings. Referring to the 'Adaptability' characteristic, Virtual Reality and Augmented Reality can enhance the adaptability of an RMS. However, not having them does not imply that an RMS is not adaptable.

3.2.2 *The perspective of sustainability*

When studying CPPS and RMS's sustainability, the term 'life cycle' is often used, which is defined by IEC 62890 as "length of time from the start of the development phase of a product type to the product abandonment". The phases of the life cycle are defined as follows [Assad et al. 2021, Schneider et al. 2019]:

- *Engineering requirements*: Specifying the goals of creating the system and its functions.
- *Specifications*: Defining the stages and manufacturing processes the product will go through.
- *Physical build*: Constructing the system and its subunits physically.
- *Commissioning*: Interfacing and integrating the subsystems and establishing the data communication channels.
- *Operation and maintenance*: Running the system and identifying the faulty components and inefficient processes.

RMS were defined in academic literature in 1999, but examining their interconnection with sustainable manufacturing is relatively new [Bortolini et al. 2018]. Regarding energy consumption, energy management for these systems was limited [Lamy et al. 2020] although the research on RMS was ongoing for the last two decades. In addition, there are different principled stands for approaching RMS's sustainability. On one hand, the assessment of reconfigurable equipment's sustainability (for both RMS and RAS) cannot be accomplished depending on the main characteristics of RMS [Olabanji & Mpofu 2020]. On the other hand, Bi [2011] and Huang et al. [2018] correlate the characteristics of RMS (e.g. convertibility, modularity, etc.) to sustainability indicators (e.g. waste, emissions, etc.). As RMS are designed to foster productivity, the methods developed to increase their sustainability should be constrained by productivity-related conditions such as cycle time. For example, Liu et al. [2019] target to minimise energy consumption cost, however, cycle time is kept minimal simultaneously. Zhang et al. [2018a] use a form of Petri nets (namely TNCES) to model and simulate a vehicle reconfigurable assembly system where energy-efficient work modes are selected, then, it is controlled while running through the minimum path in terms of time cost.

From a life cycle perspective, Battaïa et al. [2020] consider that the reuse of RMS modules in addition to their end-of-life treatment can make them more sustainable. For energy consumption, Battaïa et al. [2020] refer to the scarcity of research work that discusses reconfigurability together with energy-related constraints and identifies the following challenges:

- Defining new metrics for energy consumption to be taken into account when designing RMS.
- Proposing optimisation methods for reconfiguring the systems with the objectives of limiting energy cost or power peak.
- Proposing reactive methods for the dynamic adaptation to sudden changes of power.

According to Bortolini et al. [2018], an insignificant number of researchers began to work on integrating reconfigurability with I4.0 technologies, and this stream of research is insufficiently explored due to the novelty of I4.0. In general, RMS's sustainability assessment methods are not mature enough compared to those ones designed for assessing products' sustainability. This can be attributed primarily to the variety and complexity of those systems.

3.3 Energy management in Industry 4.0

The emerge of Industry 4.0 gave sustainable manufacturing new horizons into creating innovative methods of added-value sustainably. As explained by Stock & Seliger [2016] and depicted in Figure 3.1, the 'smart factory' will be transformed into an energy supplier in addition to being an energy consumer at the same time. Thus, supported by the smart grid, its energy management system should be capable of managing such resultant energy dynamics. Simultaneously, the embedded CPS will be customised to control value creation factors.

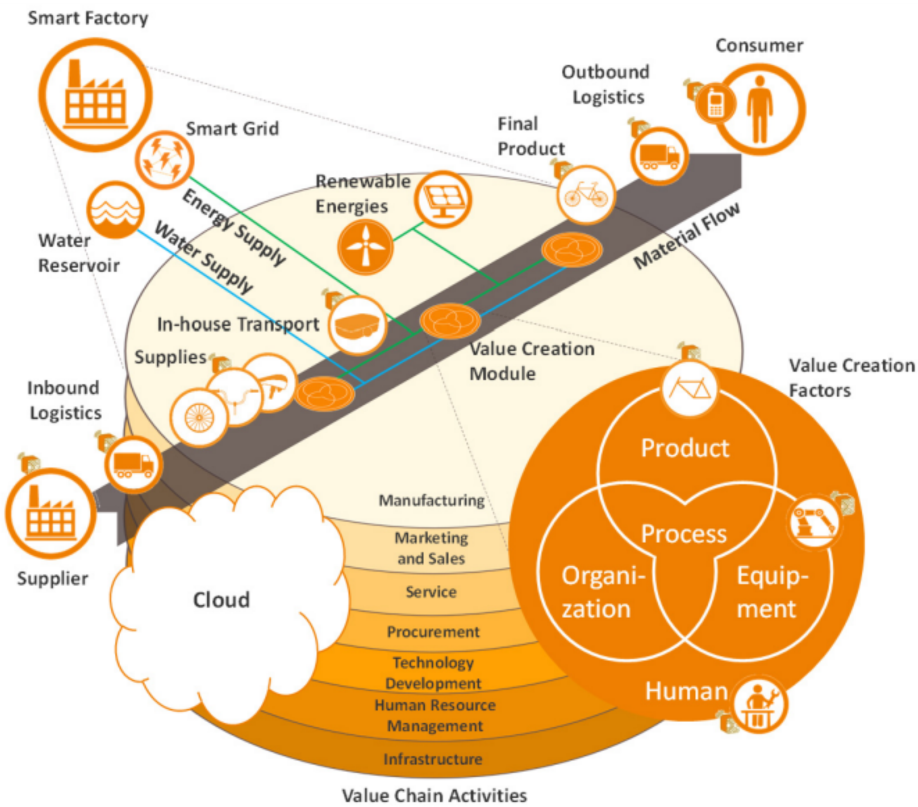


Fig. 3.1: Micro perspective of Industry 4.0 [Stock & Seliger 2016]

3.3.1 Energy management system influence on production/manufacturing

Thanks to the IoT technologies and cloud computing, monitoring of the global CO_2 emission is possible, and many major economies (e.g. China, UK, Germany, etc.) have set their targets to promote sustainable energy practices [Peter & Mbohwa 2018]. Consequently, assimilating those technologies into energy management will maintain energy security while guaranteeing the SME's competitiveness [Peter & Mbohwa 2018]. Although this thinking model has not spread to the maximum extent, some fruits of its implementation give a taste of the expected outcome. For example, Daimler in Germany reported an improvement of 30% of its robot systems' energy efficiency as a result of utilising I4.0 techniques [Medojevic et al. 2018].

A change due to I4.0 is that many tasks conventionally carried out by SCADA or desktops are moved to IoT devices [Senna et al. 2020]. So under I4.0, there is interoperability between EMS and MES where the former gathers energy data at the higher level (electrical connections) and the lower level (equipment installed in the plant), and the latter controls the production [Mendia et al. 2020]. This approach offers the potential for overall efficiency to be increased. Another indication to the influence of EMS on the production system is made by Zarte & Pechmann [2020], proposing to use energy demand profiles for production planning processes which increases the sustainability of the production system.

The term "Energy Management 4.0 (EM4.0)" is coming to life now, and is a subject of continuous improvement and innovation by investigating the very fine granularity of energy data [Nienke et al. 2017]. As Figure 3.2 shows, EM4.0 is supposed to grow from basic visibility to reach an autonomous self-optimisation accompanying the maturity of I4.0. Before I4.0, some devices such as motor actuators and air conditioners were not "smart" enough to react to real-time control signals, however, this will be changed thanks to the IoT-based solutions [Kulatunga & Sampaio 2019]. Ultimately, this constitutes the basis of founding EM4.0.

From a design viewpoint, there are two prominent types of approach: model-based approaches and data-driven approach [Medojevic et al. 2018]. Model-based approaches can be very accurate and flexible when configuring input data, however, the non-linearity and stochastic characteristics of industrial systems may complicate building those models. For data-driven approaches, they rely on understanding the trends of behaviour by means of various methods such as regression analysis, neural networks, etc. In this vein, IoT solutions support data-driven approaches by monitoring real-time system conditions.

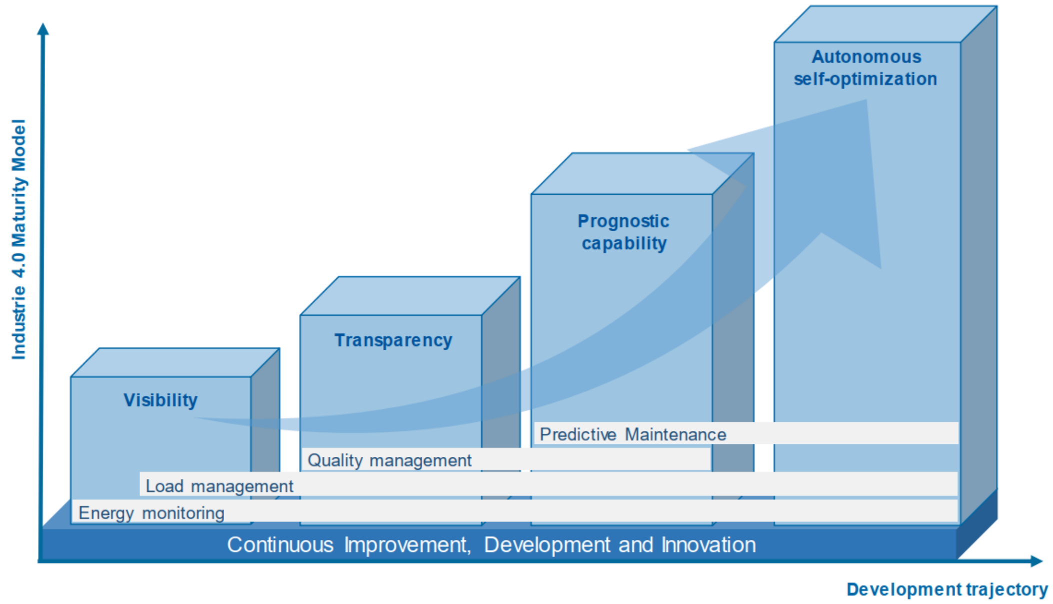


Fig. 3.2: *Industrie 4.0 Maturity Model with Energy use cases [Nienke et al. 2017, Kulatunga & Sampaio 2019]*

In the following section, the approaches of energy management implementation under I4.0 are generally categorised into their main utilised technologies and application, and the challenges to energy management under I4.0 are clarified. Afterwards, a summary table is provided to show where one technology, or a combination of more than one, is used in the same literature work. Further, a grouping of the research works according to the area of their application follows.

3.3.2 IoT

By interviewing some technology/solution providers, Shrouf & Miragliotta [2015] attempted to show the influence of IoT on energy management in manufacturing. As a result, it is shown that IoT-enabled solutions can support various functions of energy efficiency and production management decision making. As Figure 3.3 shows, for the aforementioned functions to work, preliminary captured energy data should go under the appropriate analysis to obtain a meaningful and integrable outcome. In the same vein, Tan et al. [2017] propose to integrate energy and production data so that the specific energy consumption data per time interval (e.g. hourly, daily, etc.) can be recorded, thus, energy effectiveness is evaluated.

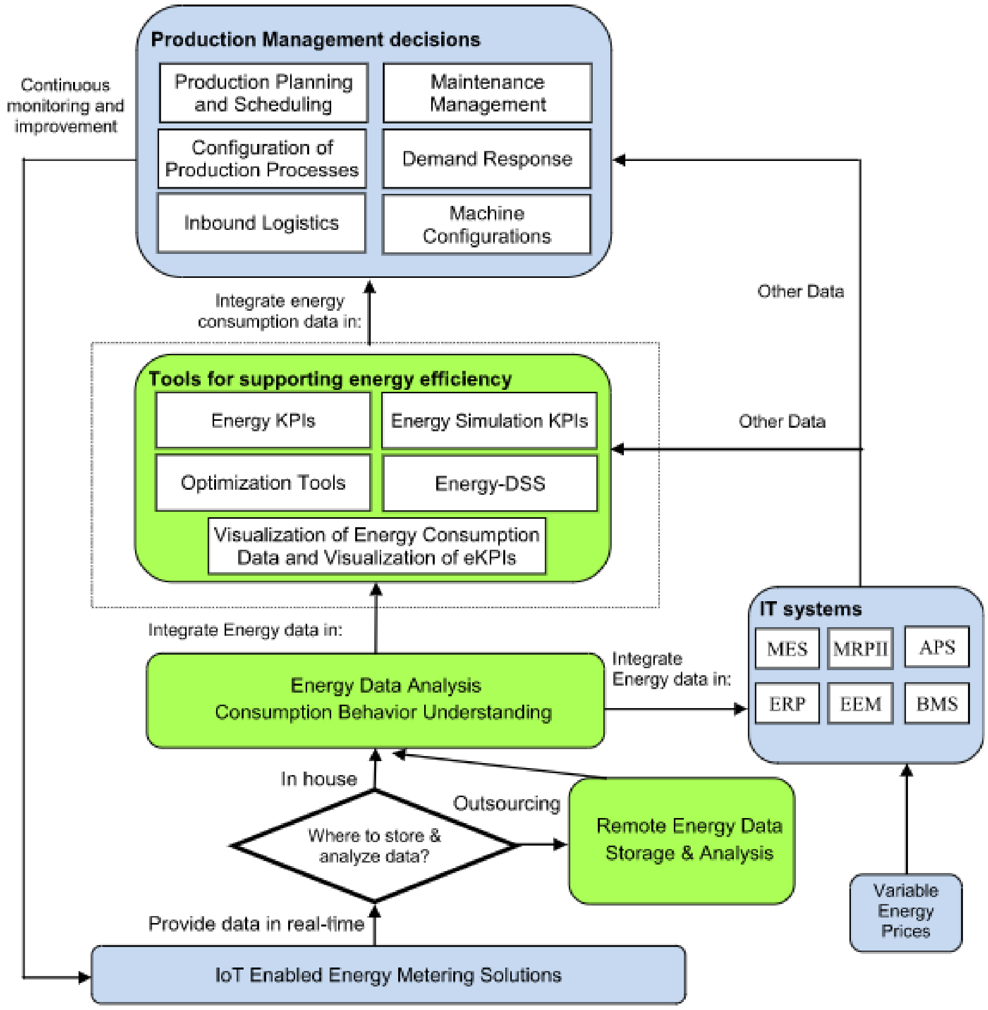


Fig. 3.3: *Framework for IoT-based energy data integration in Production Management decisions [Shrouf & Miragliotta 2015]*

At the production planning and control level, particularly scheduling, Wang et al. [2018] aim to optimise real-time energy efficiency by adopting IoT technology. To achieve this, production planning relies on the data obtained from the shop floor. Thus, a scheduling/rescheduling plan is created based on energy data. For optimising the tardiness cost and energy consumption, a non-dominant sorting genetic algorithm II (NSGA-II) algorithm is used. Miragliotta & Shrouf [2012] also refer to the IoT application's ability to configure, schedule and change machines' states. Pelzer et al. [2016] developed a 'cross energy data model' as a part of an EMS. The model objects include classes that describe the properties of power storage, power plants, manufacturing processes and their scheduling. Differential equations are used to describe the physical properties of the system's components. Thus, these equations are appropriate for optimising energy use taking into account the operational constraints.

The first step to achieving successful energy management is energy monitoring [Tan et al. 2017]. As IoT grants the opportunity of effective energy monitoring, it acts as a major enabler of achieving this. Tao et al. [2014] put forward a method for energy saving and emission reduction based on IoT and Bill of Material (BoM). In this method, the concept of Big BoM combines the data existing in each stage, the related energy consumption, the environmental impact, in addition to the basic data. Big BoM relies heavily on big data and IoT to be established. Wang et al. [2016b] present an IoT-based product life cycle energy management (PLEM). In their proposal, in the 'production' phase of the product life cycle, they highlight the fact that IoT may help to reduce idle time and define energy consumption as a function of a certain configuration.

In general, IoT devices (meters, sensors, etc.) constituted the main source of processes/equipment energy consumption data, which were later processed to support various functions of the production and energy management or their combination. Shrouf et al. [2017] discuss the idea of multi-level awareness to achieve energy efficiency. At the machine level, real-time energy data are collected with IoT smart meters, then the data are aggregated with production data at the operational level. Such an awareness affects the orientation of machinery levels (process, machine, production line, production) and product levels (operation, product, order). Kohl et al.

[2015] aim to create a maintenance technical system based on energy management data. Therefore, process-specific energy profiles are obtained by making use of the OPC UA, which eventually enables advanced efficiency predictions.

3.3.3 Utilising CPS and digital twin

With a focus on machine tools on the shop floor, Zhang et al. [2018c] utilise a set of services (e.g., energy consumption parameters optimisation and model calibration service) to interact with the data obtained from the shop-floor in addition to the physical and virtual equipment. This vision is tailored for a certain type of DT, that is the digital twin shop-floor (DTS). Also in relation to the shop-floor, Zhang et al. [2020b] include energy consumption rules in the behavioural description of the shop-floor DT. With the aim of dynamically energy-adjusted machine tool shop floor scheduling, Feng et al. [2018] established a Wireless Sensor Network (WSN) to collect data, then a tool ageing model is built and utilised together with the geometry information to schedule the production and increase the energy efficiency. A Genetic Algorithm is used to optimise manufacturing energy consumption.

Max-plus Algebra is used by [Wang et al. 2019] to make decisions of machine states (active/idle) after building it as a service in the digital space. In this approach, the DT has an event-driven energy-saving decision model which outputs the suitable decision relying on the data received from the physical system. A cyber-physical toolset for plant energy prediction and optimisation is introduced by Pease et al. [2018]. The developed toolset could monitor, predict and control the power consumption of a CNC machine for different processes. To overcome the heterogeneity of the involved devices, a variety of IoT protocols were used in a four-layer IIoT architecture.

Motsch et al. [2020] believe that the scheduling resulting from the interaction between CPPS and the production planning systems is of great importance for resource adaptation. One example of doing this is to integrate energy storage units as a separate CPS. A similar observation is made by Pei et al. [2018] where the “elastic” segments of energy production, conversion and consumption are explored, then modelled in a mathematical model in order to ensure the fulfilment of production tasks under economic and energetic constraints. The application is exemplified in a lithium battery manufacturing plant in cyber-physical environments. Zarte & Pechmann [2020] exemplify energy management using CPPS in a learning factory where energy demand is recorded, stored in a database and checked to detect the failure once it varies from the minimal and maximal energy demand profiles. In a CPS set-up, Adenuga et al. [2020] used statistical regression tools to predict the energy consumption of Variable Frequency Drives (VFD) which helps to specify the trend of energy use and supporting decision making. Aiming to decrease the difficulty of estimating the performance of CPPS encountered by the designer, Bakakeu et al. [2018] introduce a runtime engine to execute a design space exploration. One effective application of the result of the solutions implemented using the engine is to easily trade-off energy savings and other critical design constraints simultaneously.

The control systems' view of the production facility decomposes it into hierarchical levels. The interactions between the elements of a certain level impact those at the higher level, including, their energy consumption [Ocampo-Martinez et al. 2019]. Targeting energy efficiency improvement implies possessing sufficient knowledge of every level, its elements and the possible interactions. Mawson & Hughes [2019] refer to simulation as the most effective method of manufacturing processes design and evaluation, however, it is not the case when it comes to Technical Building Services (TBS) due to their continuous nature. Focusing on the machine process level, Mawson & Hughes [2019] utilised the Discrete Event Simulation (DES) with the collected energy data to improve the system's energy consumption performance. Also with DES, Karanjkar et al. [2018] constructed a DT model of an assembly line using the SimPy DES Python library where the machines (and their states) in addition to human operators are modelled. Energy consumption is controlled here by finding buffering-based optimisation solutions, i.e., identifying bottlenecks.

Considering digital twin-driven product design, Tao et al. [2018a] believe that following such an approach increases efficiency, sustainability and the design of the

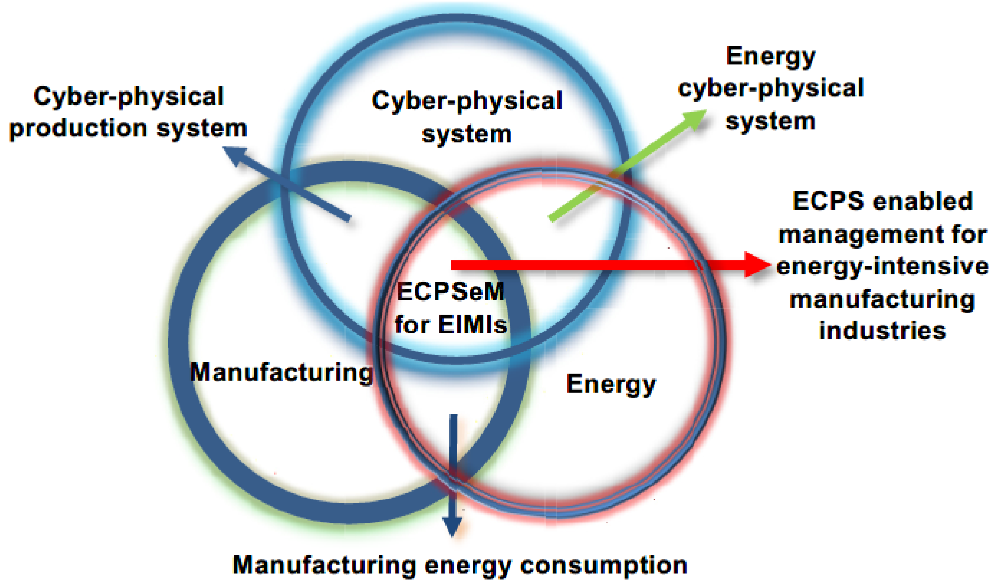


Fig. 3.4: *Interdisciplinary research areas of cyber-physical system, energy and manufacturing [Ma et al. 2019]*

product, its manufacturing and service. Barni et al. [2018] suggest integrating DT with the Life Cycle Assessment (LCA) so that DT-driven sustainability assessment and performance optimisation are achievable. Meanwhile, it is highlighted that the challenge of real environment complexity makes it difficult to create virtual spaces that can evolve with physical counterparts across the life cycle. He & Bai [2020] suggest a framework of digital twin-based sustainable intelligent manufacturing following an intensive literature review. The proposed framework maps the development of the product life cycle with the development of the manufacturing digital twin.

Nouiri et al. [2019] introduce a real-time predictive and reactive scheduling method to adapt the production's energy consumption to the energy supply (including fluctuated renewable energy). The introduced (EasySched) method involves the use of data-driven tools based on optimisation algorithms. In an interdisciplinary approach, Ma et al. [2019] theorise the energy-cyber-physical system enabled management (ECPSeM) as it is depicted in Figure 3.4. This approach is expected to contribute to green manufacturing as it takes advantage of the energy flows data and the manufacturing processes to conduct synergetic optimisations during production.

A web-based platform for knowledge sharing knowledge is introduced by Kannan & Arunachalam [2019], where a digital twin for the grinding wheel is created. By using a DT, energy consumption could be reduced by 14.4% compared to the conventional methods. Rocca et al. [2020] consider that digital technologies can support the circular economy at the factory level. Therefore, they developed an energy management application for disassembly processes. This application monitors an energy consumption indicator by means of the disassembly's DT.

3.3.4 *Web and cloud-based solutions*

In their definition of "Cloud Manufacturing" (CM), Zhang et al. [2014] included 'energy management' in the middle layer of their cloud architecture. Embedding energy data within CM allows resource integration and optimisation, resource utility rate and a knowledge-sharing mechanism [Peng et al. 2015]. Colombo et al. [2014] attempted to demonstrate the integration of legacy systems into SOA and cloud solutions through some use cases in an industrial project. One of these use cases is plant energy management in an industrial project. Their main contributions lied in energy management through cross-layer consistency management, alarm management, and scheduling of electric vehicles charging.

Delgado-Gomes et al. [2017] developed web services to perform active data exchange between the manufacturing energy management system (MEMS) and the manufacturing management system (MMS) in a way that multiple MEMS can be linked to MMS. The developed system could reduce energy consumption in the case study by 10-15%. A cloud energy management service (cloud EMS) is implemented by Tseng et al. [2016] with the ability to capture data from various devices such as control devices, lighting systems and air-conditioning. This service is responsible for the optimisation of the energy consumption of the previously mentioned systems connected to it in addition to controlling the scheduling. Furthermore, a regression analysis is conducted to specify the relationship between energy savings and the baseline of energy consumption.

Javied et al. [2019; 2018; 2016a] describe a software tool named Totally Integrated Energy Management (TIEM) which is a web application designed for monitoring and visualising energy data collected by sensors, evaluating performance indicators in addition to planning energy-related optimisation measures. TIEM is built with PHP-framework Symfony based on the DIN EN ISO 50001 standard, and designed with a modular structure to be able to perform knowledge management, energy optimisation and energy benchmarking. Another tool to estimate the impact of energy cost in a rail car manufacturing facility is introduced by Adenuga et al. [2019] as a starting point of a web-based platform. Energy data are obtained using smart energy meters from variable speed drives, lighting and HVAC equipment. A framework for data-driven sustainable intelligent manufacturing based on demand response (DR) for energy-intensive industries is proposed by Ma et al. [2020a]. On a cloud platform, a variety of applications are built including an energy monitoring application, a parameter optimisation application, and an energy warning application.

3.3.5 *Big data, AI and statistical techniques*

Energy-related big data have the "4V" characteristics: **v**olume, **v**elocity, **v**ariety and **v**alue [Zhou & Yang 2016, Zhang et al. 2018d], or "7V" when adding **v**eracity, **v**ariability and **v**olatility [Belhadi et al. 2019]. Azeem et al. [2021] identified the main areas of big data utilisation in smart manufacturing to be: predictive manufacturing environment, designing, smart planning, smart quality control, smart maintenance, sustainability and smart scheduling.

Flick et al. [2018] introduced a framework for classifying equipment according to the energy management value based on the literature and the international standards (e.g., ISO 500001). In this study, robots are found to provide energy consumption data per cycle and the actual power, thus, they could achieve a high rating in terms of energy reduction potential (according to the framework).

Combining big data analytics and IoT enables the shift from diagnosis to prognosis in controlling energy consumption, thereby, energy cost [May et al. 2017]. Bevilacqua et al. [2017] attempted to integrate big data and IoT assisted by enterprise data cloud. Data obtained from the machines were collected for different configurations so that the most efficient one can be identified. Besides, production energy waste due to the idle time and the energy consumed for producing one product could be specified. Once integrated into expert systems, AI-based data-driven services give in-depth information about energy demand patterns and which can be classified into [Senna et al. 2020]:

- Predictive analytics (prognostics): including modelling uncertainty and correlating the state parameters with energy consumption.
- Prescriptive analytics: including self-control of energy consumption and root-cause analysis of unusual energy consumption.

Mendia et al. [2020] believe that developing methodologies that rely on ML can sustain industrial production while reducing the energy cost to its minimum. Therefore, a three-layer architecture for energy monitoring and consumption evaluation is proposed where the base layer contains IoT technologies, sensors and smart meters. Zhang et al. [2020a] develop a method to detect hybrid data association (i.e. production data and energy consumption). Also, a big data-driven analysis is conducted by means of Deep Belief Networks (DBN) in order to detect production anomalies. A variety of prediction methods such as regression, decision tree and random forest are used by Ma et al. [2020b] with the support of big data which can enable the transformation of data into information and knowledge. The acquired knowledge influences decision-making at the highest level of the hierarchy which contains energy supply control and energy demand prediction applications.

Neural Networks (NN) were used by Yu et al. [2017] to search for power-saving opportunities by analysing big data associated with semiconductor production. By identifying the relationship between the input parameters and the power consumption per toolset move, the best setup can be chosen. In the context of the Learning Factory, Brüggemann et al. [2020] introduce a group of modules aimed at achieving resources efficiency through digitalisation. In one of these modules, training on data mining from big data is offered in addition to AI (e.g. classification and pattern recognition). A framework for capturing big data across the product life cycle is developed by Zhang et al. [2017] in order to make optimised life cycle decisions. Furthermore, discovering the hidden relationship between the data elements helped to reduce material, water and power consumption. Cloud-based simulations for energy consumption and production quality modelling are introduced by Şen et al. [2019] where a simulation feedback loop could be established using measurement nodes to communicate with the cloud in two directions.

3.3.6 Summary and discussion of the technologies used for energy management

Table 3.2 summarises I4.0 technologies and their main application field in the research investigated earlier. These technologies include CPS and their main constituents, i.e., Digital Twin (DT), Internet of Things (IoT), Web and Cloud utilisation, and Artificial Intelligence (AI)/statistical methods, in addition to Big Data.

These technologies were chosen based on their popularity in the field of modern manufacturing.

The analysis of the previous research works investigated in this section makes it possible to group them into different target groups as follows:

- *Improved Scheduling*: This is found in the following works: Colombo et al. [2014], Oh & Son [2016], Pelzer et al. [2016], Pease et al. [2018], Feng et al. [2018], Karanjkar et al. [2018], Pei et al. [2018], Wang et al. [2018], Zhang et al. [2018c], Ma et al. [2019], Ocampo-Martinez et al. [2019], Mawson & Hughes [2019], Nouiri et al. [2019], Wang et al. [2019], Rocca et al. [2020], Senna et al. [2020].

  Scheduling is directly linked to machine states (e.g., idle, active). As these states are easily detected and reported thanks to IoT, then by switching to a different state using DT for example, it becomes possible to opt for a more sustainable setting in terms of sustainable energy consumption. Moreover, simulation techniques such as DES can be used more effectively due to the

Research Work	**Industry 4.0 Technology**			
	DT/CPS	**Web/Cloud**	**Big Data**	**IoT**
Colombo et al. [2014]	–	✓	–	–
Tao et al. [2014]	–	–	✓	✓
Kohl et al. [2015]	–	–	✓	✓
Shrouf & Miragliotta [2015]	–	–	–	✓
Javied et al. [2016a]	–	✓	–	✓
Tao et al. [2016]	–	–	–	✓
Tseng et al. [2016]	–	✓	–	–
Pelzer et al. [2016]	–	–	–	✓
Wang et al. [2016b]	–	✓	–	✓
Bevilacqua et al. [2017]	–	✓	✓	✓
Delgado-Gomes et al. [2017]	–	✓	–	–
Shrouf et al. [2017]	–	–	–	✓
Tan et al. [2017]	–	–	–	✓
Yu et al. [2017]	–	–	✓	–
Zhang et al. [2017]	–	–	✓	–
Bakakeu et al. [2018]	✓	–	–	–
Barni et al. [2018]	✓	–	–	✓
Feng et al. [2018]	✓	–	–	–
Flick et al. [2018]	–	–	✓	✓
Javied et al. [2018]	–	–	✓	✓
Karanjkar et al. [2018]	✓	–	–	✓
Pease et al. [2018]	✓	✓	–	✓
Pei et al. [2018]	✓	–	–	–
Tao et al. [2018a]	✓	–	✓	–
Wang et al. [2018]	–	–	–	✓
Zhang et al. [2018d]	–	–	✓	✓
Zhang et al. [2018c]	✓	–	–	–
Adenuga et al. [2019]	–	✓	–	✓
Javied et al. [2019]	–	✓	–	✓
Kannan & Arunachalam [2019]	✓	✓	–	✓
Kulatunga & Sampaio [2019]	–	✓	–	✓
Ma et al. [2019]	✓	✓	✓	✓
Nouiri et al. [2019]	✓	–	–	✓

Table 3.2 (continued)

Research Work	Industry 4.0 Technology			
	DT/CPS	Web/Cloud	Big Data	IoT
Şen et al. [2019]	–	✓	–	✓
Adenuga et al. [2020]	✓	–	–	✓
Ma et al. [2020a]	–	✓	✓	–
Mendia et al. [2020]	✓	–	–	✓
Motsch et al. [2020]	✓	–	–	–
Rocca et al. [2020]	✓	–	–	–
Senna et al. [2020]	✓	–	–	✓
Zhang et al. [2020a]	✓	–	✓	–
Zarte & Pechmann [2020]	✓	–	–	–

Concluded

Table 3.2: *Classification of research works on energy management under Industry 4.0 according to the utilised technologies*

possibility of dynamically updating simulation models, thus, increasing their accuracy.

Optimisation of scheduling is applicable in many sections of the production facility and can be an effective tool of energy management. For example, as suggested by Oh & Son [2016], a co-optimisation between manufacturing planning and energy management can be conducted, however, planning complexity may hinder the wide acceptance of this approach.

- *Life cycle design*: mostly focused on product and regarding manufacturing the system's part of it. These are: Tao et al. [2014; 2016], Tseng et al. [2016], Delgado-Gomes et al. [2017], Zhang et al. [2017], Barni et al. [2018], Tao et al. [2018a], Kannan & Arunachalam [2019], Senna et al. [2020], Wang et al. [2016b].

  The approaches whose focus is life cycle focused on product life cycle giving less attention to manufacturing/ production system life cycle. One might argue that the system's life cycle is contained in the product's life cycle, however, the system has to be equipped with its own mechanisms of preserving sustainability for a certain range of products. Indeed, systems are reconfigured to adopt new products. Meanwhile, systems' engineering tools vary from those for the product, thus, more attention should be given to the system life cycle particularly in terms of sustainability design rather than discussing this only for the product. Another argument to be mentioned here is that system's components/units themselves are 'products' and 'services' of other systems. Consequently, they hold some sustainability aspects if sustainability design principles are applied when building them. I4.0 has tackled this philosophical dilemma by introducing AAS that can represent either product or system.

IoT-based energy management is still at a primitive stage [Tao et al. 2016]. It is well known that there is a strong link and interaction between the life cycles of the product and the manufacturing system life cycle. Thus, energy management can go in parallel for both. The scientific literature indicates that DT can contribute to sustainability in the context of the life cycle but energy management is not particularly targeted. Product life cycle management (PLM) suffers from a lack of awareness of energy consumption [Tao et al. 2016]. As a result, the manufacturing system life cycle will be negatively influenced.

- *Data-related operations*: such as data mining, envelopment and creating analytics and predictions using statistical techniques or artificial intelligence and knowledge management. These are: Javied et al. [2016a], Tao et al. [2016], Tseng et al. [2016], Tan et al. [2017], Bevilacqua et al. [2017], Yu et al. [2017], Bakakeu et al. [2018], Flick et al. [2018], Javied et al. [2018], Pease et al. [2018], Zhang et al. [2018d], Adenuga et al. [2019], Javied et al. [2019], Ma et al. [2019], Adenuga et al. [2020], Brüggemann et al. [2020], Senna et al. [2020], Mendia et al. [2020], Adenuga et al. [2020], Ma et al. [2020b;c], Zhang et al. [2020a].

  Smart manufacturing is data-driven manufacturing [Tao et al. 2018b]. Consequently, a significant contribution of data-related processes (e.g., mining, storage, processing) is expected. Data acquisition was possible in conventional manufacturing, however, under the abundance of data generated by IoT devices, and the capabilities provided by Cloud Manufacturing (e.g. storage, computation), have helped to make decisions timely and precise. More importantly, data availability has enabled to use of AI and advanced statistical methods to correlate a variety of parameters that influence energy consumption.

- *Production planning, control and management*: as in Shrouf & Miragliotta [2015], Bevilacqua et al. [2017], Delgado-Gomes et al. [2017], Shrouf et al. [2017], Pei et al. [2018], Ma et al. [2020b;a], Motsch et al. [2020], Senna et al. [2020], Zarte & Pechmann [2020].

  In addition to scheduling, Production Planning and Control (PPC) involves managing other resources such as raw material and capacity planning. Resources' traceability enables planning their consumption sustainably, and profitably. Therefore, energy can be treated as a resource to be managed, whether consumed by machines or TBS. In a more advanced scenario, energy has its own cyber-physical system that collaborates with the production/manufacturing system by exchanging data with it in order to optimise energy consumption.

- *Maintenance*: Colombo et al. [2014], Kohl et al. [2015], Nienke et al. [2017], Zhang et al. [2017], Pei et al. [2018], Kulatunga & Sampaio [2019], Zarte & Pechmann [2020]).

  The normal behaviour of a component/machine is typically linked to a certain level of energy consumption at a certain capacity. Smart meters and IoT sensors enable fault detection systems to trigger alarms as soon as an anomaly is detected. Anomalies are not only linked to a timely state but also to a pattern of energy consumption. In addition, the computation time and capability could restrict the timely processing of anomalies, in addition to data transfer problems. With the applications built in the cloud, such problems can be overcome.

In relation to the objectives identified earlier in 1.2.4, the achievement Objective 2 requires an understanding of the capabilities of ICTs in addition to their possible utilisation fields. By analysing the current status of energy management under Industry 4.0, it can be understood that more attention is given to production-related activities (e.g., scheduling, maintenance, PPC, etc.). Therefore, additional care should be given to proactive design approaches. Also, while targeting a component-based design of the manufacturing system supported with Industry 4.0 technologies, its position in the landscape of energy management has been clarified. Subsequently, advancing component-based design towards energy flexibility (beyond energy management) should attempt to cover the analysed research gaps (detailed in 3.6).

3.3.7 Challenges to Industry 4.0 energy management

Although energy management is advancing with the support of Industry 4.0, this comes with some challenges and threats to be considered when adopting the paradigm of Industry 4.0.

In general, the cost of energy is still low compared to the manufacturing added-value. Consequently, meeting the market demands and schedules still occupies the highest priority [Oh & Son 2016]. A major concern associated with I4.0 is data security and privacy. This continues to affect energy management which makes companies a vulnerable target for hackers who threaten their intellectual property [Medojevic et al. 2018]. As a result, industrial standards and data security infrastructure have to be established [Javied et al. 2018]. Physically, energy management is difficult as storing energy and changing its state are not straightforward [Oh & Son 2016]. Furthermore, the complexity increases as renewable energy resources are integrated. For SMEs, one challenge is the economic viability of auch technical expenditure [Hasan & Trianni 2020].

Manufacturing processes generate a great amount of energy data at a high speed which can be classified into [Ma et al. 2020a]:

- Structured data: including timestamped energy consumption data.
- Semi-structured data: including data exchanged between smart energy management platforms.

- Unstructured data: e.g. ethical constraints data.

The high volume, variety and heterogeneity of these data make them difficult to mine, therefore, data-driven collection methods and processing are recommended [Ma et al. 2020a]. Additionally, the majority of energy management plans in manufacturing are still theoretical [Ma et al. 2020c].

3.4 Manufacturing energy flexibility

The aim of this section is to investigate research contributions to energy flexibility (EF) taking into account the level of involvement of digital manufacturing, digitalisation or virtualisation. Thus, it becomes feasible to compare EF status from the perspective of smart manufacturing. Another target is to categorise the research works in accordance with their area of focus on the way to identifying the research trend they belong to.

3.4.1 Production planning and control

Keller et al. [2016b] propose energy-oriented production control where energy consumption is treated as a design parameter. This scenario is tested with a simulation study performed with the Technomatrix Plant Simulation software. This vision is extended in Keller & Reinhart [2016] by sharing information between the so-called computer-based systems: Supply Chain Management Systems (SCM), Enterprise Resource Planning Systems, (ERP), Manufacturing Execution Systems (MES), and Production Data Acquisition (PDA). It can be noticed here that there is a clear shift to higher control levels, e.g., supply chain. Nevertheless, Keller et al. [2017] believe that the focal point for successful integration of the energy flexible manufacturing system with the smart grid is the PLC, which acts as the data node. They they exemplify a procedure of how PLC interaction with Production Planning and Control (PPC) can serve EF.

Also focusing on production control, Schultz et al. [2017b] believe that minimising the deviation in energy consumption reduces energy costs, and this can be achieved through controlling the production by introducing the “load deviation” parameter. In fact, this parameter depicts the difference between the planned and the actual load profiles. The approach proposed by Schultz et al. [2017b] is validated using the material flow simulation tool Tecnomatix Plant Simulate®.

Bank et al. [2019] found that in most of the cases, simulation-based optimisation yields a result that is close to the optimal solution. To minimise energy costs, Schultz et al. [2016] propose an energy-oriented approach that aims at load management as a function of production control, energy supply and shop floor data. This in turn leads to eliminating the deviation of the predefined energy schedule, thus, no additional costs are incurred. As on-site generation and energy storage can enhance energy flexibility, Keller et al. [2016a] believe that it can be used to integrate the energy market with PPC. Therefore, an integration model that specifies the PPC tasks corresponding to the energy plan is introduced. Depending on the fact that most MESs can capture energy data, and the possibility of forecasting energy prices up to 15-30 minutes in advance, Schultz et al. [2017a] suggest a four-module production control system architecture that allows load control by means of EF data and demand monitoring. To optimise load management, the Branch & Bound algorithm is used to find the optimal solution.

To support the production manager in identifying the potentials of EF, a four-step method that is based on system dynamics modelling is presented in [Simon et al. 2019]. The system model produced by this method should adapt to the influencing factors by manipulating a set of variables. Some of the influencing factors considered by Simon et al. [2019] are production utilisation and product quality. In the context of PPC, Simon et al. [2017] identified a set of measures for EF evaluation, then the interaction between those measures was analysed. Those measures are generated by the operator who specifies their threshold as a function of the energy market status. Another set of measures are introduced by Rackow et al. [2015]. The measures of energy flexibility were reviewed earlier in section 2.2.4. Considering the available EF measures, a risk inventory and a list of preventive countermeasures, Roth et al. [2021] used Bayesian network theory to model the possibility of risk measure paths and visualised the results in an application built with Matlab.

3.4.2 Scheduling

Although 'scheduling' can be regarded as one of the PPC tasks as clarified earlier in 2.2.3, this section is included for it, due to the fact that the research works mentioned below focused on scheduling in particular.

System parameters (e.g. buffer capacity and system utilisation) in addition to scheduling the processes are proposed by Beier et al. [2017]. The aim here is to maintain the production system throughput while receiving electrical energy feed from on-site variable renewable energy (VRE) sources. Lombardi et al. [2019] propose to increase the capacity of buffer stocks which gives the manufacturing process more flexibility on the way to achieving the "net zero energy factory". Besides, they believe that smart transformers and energy storage systems can further support flexibility options.

A mixture of DSM, VRE re-dimensioning and battery storage utilisation is conducted in [Schulze et al. 2019b]. For DSM particularly, manufacturing processes can be switched off if VRE generation is not enough. In relation to energy storage sizing and dimensioning as well, Zimmermann & Sauer [2020] propose a three-step methodology of peak shaving for grid charge reduction. These steps include load profile analysis, storage system power and storage system capacity. In a warehouse, Carli et al. [2020] developed an optimisation model that allocates the optimal schedule of battery charging of an electrically-powered material handling equipment. The optimisation model takes into account the time-dependency of electricity prices with two different tariffs being applied.

Also relying on machine scheduling for further energy flexibility, Keller et al. [2015] attempted to optimise the schedule using the Simulated Annealing algorithm under the constraints of working time and production jobs. A job-shop scheduling model that considers various machine operation modes is introduced by Grosch et al. [2019]. The machine's operation mode is chosen depending on the model of machine energy consumption. The solution of the proposed model is found using a Genetic Algorithm (GA).

3.4.3 Machine tool

For machine tools, Popp et al. [2017] rely on Energy-Independency-Indicator (EII) adopted from Popp & Zaeh [2014]. EII is calculated for components that have controllable energy demand. In this concept, the component is assumed to be a part of the machine tool, e.g., spindle [Verl et al. 2011]. Thus, the approaches proposed in Popp et al. [2016; 2017] depend on prolonging or shortening and interchanging the periods of activity and passivity taking into account the demands of machining operation. This approach is demonstrated using a Matlab simulation model. Also, this approach is further used in [Popp et al. 2018] when discussing EF at multiple levels namely: component level and machine level. Taking into account shop floor reconfigurability, Lamy et al. [2020] attempt to minimise the total production time (to maintain productivity) under certain energy thresholds. It was found that small-scale problems (involving three machines and their jobs) can be solved using linear solvers. Materi et al. [2020] discussed the influence of supply energy on the machine tool operation parameters e.g. cutting speed. Thus, they built a numerical model to correlate the productivity (represented by cutting speed) with the available energy obtained from renewables. The demand is calculated from a discrete uniform distribution, and the buffer is the remainder from the previous day.

For other types of machines (e.g. thermoforming), Brugger et al. [2017] propose to analyse the process step and rely on the control programme to analyse energy flexible process steps. Besides, a forecast model of each component is necessary to optimally use EF options. Although a lot of effort is put into using scheduling techniques to improve energy sustainability, neither an indication of the corresponding control is made nor an explanation of the expected approach is provided. Regarding control particularly, Ivanov et al. [2021] state that currently, the way control methods can be applied to formulate scheduling accurately is not clear enough. As a result, the same problem can be expected to happen when scheduling manufacturing activities for increased EF.

3.4.4 Manufacturing style and structure

In response to the Factory of the Future (FoF) where IoT technology is fully utilised, Schulz et al. [2018] suggest using an IoT-based control loop. For the validation, three control strategies are identified and simulated in the ThingsSpeak IoT platform. Those control strategies are all based on the components' energy consumption and potential configurations.

Another route to achieving energy sustainability is by managing the relationship between the demand and supply parties. Beier et al. [2016] suggest using the electric vehicles'(EV) storage capability to eliminate the difference between demand and supply. The EV fleet is charged/discharged depending on the VRE outcome and manufacturing system needs. This approach is tested on an experimental manufacturing lab with connected VRE (wind and solar) generation and the EV fleet. Roesch et al. [2019] established an Energy Synchronisation Platform (ESP) that provides services related to delivering energy-oriented manufacturing. This platform differs from the existing IT platforms as it considers the management of industrial manufacturing processes. An example of these services is the EF management one responsible for the technical assessment of flexibility. Unterberger et al. [2017a] state that EF should be established starting from the factory planning stage in terms of having transparency about the energetic features. Therefore, EF should be modelled and analysed and the necessary measures have to be defined. In support of this concept, harmonising the energy provision system and production system in terms of objectives, data, solutions and concept development is introduced in [Unterberger et al. 2014].

Given the recent changes in power electronics, "microgrid" is becoming implemented on industrial sites that utilise renewable energy resources. Weckmann & Sauer [2019] discuss this point taking into account the centralisation/decentralisation of the control system. Thus, they turn the focus into the DC-Grid control and attempt to control the voltage level. The production machine's states are varied to control energy consumption.

According to Pierri et al. [2020], most of the work done on EF considers discrete manufacturing use cases and a small part of gives attention to the process industry, where the work methodology is different. For this particular type of industry, assessing of possible integration of VRE is carried out in Pierri et al. [2021].

3.4.5 Technical building services

As Technical Building Services (TBS) consume a significant share of industrial energy, this justifies investing in energy flexibility [Thiede 2012]. Schulze et al. [2019c] rely on data analytics to understand a hybrid cooling tower behaviour and then predict the system behaviour. Next, EF management strategy can be planned. Focusing on the design phases of TBS, Flum et al. [2018] propose a model-based approach that can be integrated with factory planning. This approach starts with identifying the available energy options (price and quantity), energy flexibilisation technological means and configurable parameters. Then, a simulation and evaluation scenario is performed. Apart from the production-related EF in terms of control and scheduling, Weeber et al. [2017] identify the peripheries of EF to be: centralised auxiliary processes (e.g. cascaded compressor station), supply technologies (e.g. pipes of thermal liquids), decentralised auxiliary processes (e.g. vacuum pumps with tanks), technical building services (e.g. HVAC) and building shell.

An energy management system that works on flexibilising energy is presented by Schulze et al. [2019a]. The concept is based on prioritising energy feed sources as follows: on-site VRE (1^{st}), available VRE (2^{nd}), grid feed (3^{rd}). Blume et al. [2020] developed a data-driven digital twin for industrial cooling towers to make the most of their possible contribution to EF. Data mining was used to predict performance KPIs and a business analysis was conducted.

3.4.6 Life cycle

Aiming to integrate EF in manufacturing system and product life cycles, Rödger et al. [2020] consider that manufacturing simulation can cover both, therefore, the processes' energy demand is modelled by means of their states (e.g. on, off) where energy consumption is either fixed or variable. To validate this approach, 14 scenarios that include energy feed from volatile sources were tested. An IT platform to support the synchronisation between the company side and the market is introduced by Bauer et al. [2017]. The proposed architecture relies on a Service-Oriented Architecture and provides Life Cycle management as one of the base services.

3.4.7 Flexible factories and interaction with the communities

A simulation model is developed by Roth et al. [2019] in order to assess the possible scenarios of energy flexibility application in a specific region by entering the available energy supply. Following the identification of the flexibility measure, an optimisation of the residual load is performed. It can be noticed that load forecasting plays an important role in deciding the potential of EF when studying the demand side. Aiming to support decision-making by forecasting the short-term load of machine tools, Dietrich et al. [2020] utilise a mix of time series and machine learning (namely Random Forest (RF) and Artificial Neural Networks (ANN)). To do so, the required features include the electric load of machines and components, the control signals and some physical properties (e.g. temperature, speed, acceleration, etc.).

3.4.8 Discussion and summary

In this section (3.4), EF research has been categorised into different groups depending on the focus of the analysed research works. Comparing these fields of application to the ones analysed earlier in 3.3, it can be noticed that the themes of intersection are particularly scheduling, production planning and control and life cycle confederation. Indeed, EF involves a sort of energy management with focus on VRE integration and utilisation in various aspects of manufacturing system and the plant.

Assistive energy storage (e.g. compressed air, batteries) aids in achieving EF. It acts as a balancing mechanism to compensate for the shortage of energy provision and can help to store the excess energy from on-site generation. In principle, such

Literature work	Control level	Application means
Brugger et al. [2017]	Machine level	Analysis of machine modules to identify energy flexible process steps
Beier et al. [2016]	Manufacturing system, EV fleet	Modelling the dynamics between VRE supply, EV and manufacturing system
Beier et al. [2017]	Execution/real-time	Process and buffer behaviour adjustment
Dietrich et al. [2020]	Machine and component	Forecasting short term load profile
Grosch et al. [2019]	Machine	Switching machine operation modes according of energy prices
Keller et al. [2016b]	MES and ERP	Comparing energy consumption with MES's machine operation data
Keller & Reinhart [2016]	SCM, ERP, MES and PDA	Information sharing between the computer-based systems
Materi et al. [2020]	Machine tool and component	Varying the operation machining parameter considering the economic effect
Popp & Zaeh [2014]	Component	Calculating EII and assessing EF potential
Popp et al. [2016; 2017; 2018]	Machining level and component	Shifting activity periods of machine components
Roesch et al. [2019]	Company level, manufacturing processes	ESP
Schultz et al. [2016; 2017b]	Production control	Load control, Generating manufacturing jobs based on the energy schedule
Schultz et al. [2017a]	Production control, MES	Optimised load management
Schulz et al. [2018]	Component	Component's mean power difference, and its possible configurations
Schulze et al. [2019b]	Manufacturing processes	Installing product buffers and switching the processes' states (e.g. “stand by”)
Unterberger et al. [2014]	Manufacturing system	Harmonising energy system and production system
Unterberger et al. [2017a]	Manufacturing system	Creating a matrix of energy demands and strategies
Weckmann & Sauer [2019]	Production processes and DC-Grid	Varying the voltage level depending on energy price
Zimmermann & Sauer [2020]	Energy storage system sizing	Peak shaving by integrating an electric storage system

Table 3.3: *A summary of control level used in literature to achieve energy flexibility*

a capability is extremely useful for PPC, scheduling and TBS. Another support mechanism is the possibility of switching between multiple sources of energy (e.g. between electricity gas).

At the technical level, Table 3.3 summarises the control level suggested in the studied literature and its suggested means of application. It is noticeable that the finest level of EF application can be "component level" but mostly in the case of machine tools. More tendency is towards PPC and scheduling. Also, similar indications to the possible coordination between the production system and energy system are found.

The mechanisms of configuration are not given enough attention except in few cases such as Schulz et al. [2018] where it is proposed to make use of the IoT technology. Otherwise, achieving the transition to new schedules or production plans is not fully explained especially in relation to the control verification.

Regarding life cycle consideration, it is suggested to merge manufacturing system simulation and life cycle assessment in Rödger et al. [2020] which is a method of improving sustainability. However, there is no design perspective, especially with regards to manufacturing system design.

3.5 Energy consumption of electric drives

Electric drives (EDs) are essential components of modern manufacturing systems. They are noticeable in robots, CNC machines and multiple motion control applications [Assad et al. 2018]. As the automation of manufacturing continues to grow, EDs' energy consumption should be taken into account. According to Javied et al. [2016b], around 70% of the electricity required in industry is consumed by EDs. Table 3.4 below shows the potential savings from electrically driven systems.

Potential savings from electrically driven systems	**Potential savings in %**
Increased use of energy-efficient motors	10
Electronic speed control	30
Mechanical system optimisation	60

Table 3.4: *Potential savings from electrically driven systems [ZVEI 2015]*

As it can be noted that the potential for improving EDs' energy consumption is high. Furthermore, in a more advanced scenario, once engaged in energy flexibility, a variety of their applications can be harnessed. Literature works have explored and analysed ED's energy consumption across their applications over the last two decades. In industrial robots for example, for the last 15 years, motion planning optimisation aimed to mainly reduce energy consumption by developing efficient path planning and collision-free motions [You et al. 2011, Verscheure et al. 2009, Paryanto et al. 2015].

Generally,the energy losses of drives are classified into [Paryanto et al. 2015]: core losses, stray load losses, stator losses, windage and friction losses, and rotor losses. Those losses can be analysed and studied by electrical machines designers and power electronics specialists. However, for manufacturing systems developers, EDs are considered components to be sized and selected carefully at the design phase. Therefore, the aim of this section is to look into some of these works with more focus on the manufacturing system design perspective, and to verify the state of ED's use for EF purposes. The technical perspective considers the problem of an independent manufacturing unit (e.g. robot, CNC, etc.), where this unit's energy consumption has to be improved by using trajectory design methods for example. Whereas the system development method looks further ahead by realising the studied unit as a component of a manufacturing system that will go through changes in the future. Thus, building on the conclusions derived at the technical level, it is desirable to shorten the development time and save effort whilst maintaining acceptable energy consumption behaviour.

3.5.1 Trajectory-based design methods

A plethora of work has been done in the field of trajectory design for the purpose of energy consumption reduction. Some of these works will be covered here as trajectory optimisation for different purposes (e.g. minimum time, minimum jerk, etc.) is an independent subject in itself. The advantage of the motion planning approach is that its implementation does not require the modification of the mechanical system by adding or substituting physical components [Carabin & Scalera 2020].

The resistive losses of the drive vary depending on the motion, axis speed and torque profile. Therefore, Hansen et al. [2012] referred to the necessity of including these losses in the robot's energy consumption model. To optimise energy consumption, initial trajectories (trapezoidal acceleration motion profiles) are reproduced using B-spline parameters. A non-linear optimization problem is formulated in [Hansen et al. 2013] in order to reduce the energy consumption of a two-axis test rig. The formulated cost function contained the mechanical losses in addition to the servo drives losses. Using the modelling of an electromechanical system, energy formulation is found by Carabin & Scalera [2020]. Two designed trajectories (namely trapezoidal and cycloidal) were tested for the validation of the built model where an energy reduction of 33.6% could be achieved. For Cartesian robots driven by DC motors, Boscariol & Richiedei [2019] utilised spline-based trajectory planning algorithms. Optimisation was then performed and a comparison was conducted based on the consumed energy and the elapsed time.

Using polynomial curves (3^{rd},5^{rd},7^{th} degrees) for motion planning, Hosseini & Hahn [2018] showed the drawbacks of using such curves and checked their energy efficiency. To achieve this, they used an energy model that considers energy dissipation resulting from resistive windings besides the stator and rotor iron losses. Also for different order polynomials, the Euler-Lagrangian method is applied in Hosseini & Hahn [2019] to find the corresponding energy consumption. Consequently, the losses could be reduced by 29%.

Berselli et al. [2016] proposed an approach that relies on SolidWorks and Matlab software tools to find the mechanical system properties and to compare the energy consumption of various spline trajectories. Such an approach can be used for prototyping systems and enables future reconfigurations.

Like other fields in manufacturing, motion control and motion planning are affected by Industry 4.0 and its enablers. Consequently, remarkable computational abilities in terms of storage and processing became available to be used by the manufacturing system components using the Service oriented Architecture (SoA). Among the case studies related to ubiquitous manufacturing systems based in the cloud, Wang et al. [2017] introduced an approach to minimise the energy consumed through the robot movements by finding the best configuration for the robot joints. Further integration between the layers of the manufacturing system, i.e., the manufacturing cell layer, the production process layer and the workshop layer can be found in Zhang et al. [2018b] where a cross-layer optimisation model was suggested.

3.5.2 *Virtual engineering and system development approaches*

Damrath et al. [2014] realise the need for energy prediction tools in the system's design phase. Therefore, physics-based virtual engineering and virtual commissioning (VC) are utilised assisted by a physics-based engine to evaluate energy consumption. Then, their applicability is tested by exemplifying a robot trajectory. Also using physics-based virtual engineering, energy consumption units (ECUs) are defined by Damrath et al. [2016] from the BoM (including electric and pneumatic drives). Afterwards, and seeking to build an energy model of the assembly system, energy component models have to be established. In another research on automated production systems in the VC phase, Sinnemann et al. [2020] aimed to increase the potential of energy consumption optimisation by developing an architecture for energy simulation. This architecture is tested by controlling an industrial robot performing various tasks at different speeds.

Hauf et al. [2015] use the *Vcom* tool which is a chain of a combination of software tools for integrating various data types (e.g., PLC and industrial robot programmes). By integrating energy models of a servo drive, the energy consumption profile can be visualised, then in the future, energy consumption can be reduced and optimised. Performing simulations in *Process Simulate* (Siemens), Benzerga et al. [2017] could achieve an energy consumption reduction by testing the impact of the robots' motion velocity and acceleration changes. Besides, they highlight the importance of having a self-learning algorithm related to the PLC programme so that velocity can be adjusted dynamically. In the process of developing mechatronic components Functional Mock-Up Units to reach a high accuracy of the behaviour models, Süß et al. [2016] exemplify the use of industrial robot energy consumption manufacturer models in the VC process. Once energy simulation is integrated with VC, VC is extended to become energy Virtual Commissioning (eVC) which is demonstrated on a turntable in [Hauf et al. 2017a]. To enable energy simulation, Functional Mock-up Units (FMU) are needed. FMUs are exchangeable simulation models developed within the EU research project MODELISAR [Hauf et al. 2017b] according to a specific standard and enable the simulation of physical and energy behaviours among many others.

In [Ghani et al. 2012], the information related to accelerations, inertias and torques are imported from the VE environment for each simulated device. Consequently, the energy consumption could be estimated according to the predefined process sequence. An algorithm that takes into account the drive type, motion profile and torque is proposed by Ghani & Sheikh [2014] where the motion profiles are provided by the virtual system. Then, the VE component's model supports the establishment of the stations DES energy consumption model. To be able to integrate the component's drive energy consumption in a VE model, Ahmad et al. [2015] analysed it and proposed a framework for achieving this in the vueOne VE software tool. Then, the applicability is tested in a pick-and-place robotic station.

As a brief conclusion to this section (3.5), trajectory design for EDs' energy consumption improvement continues to develop. Recently, digital technologies have contributed to its application. For manufacturing, this results in greater flexibility provided by electrical drives applications in terms of the ability to change their energy consumption behaviour as a function of the chosen motion profiles. Further, there is a requirement stemming from manufacturing systems developers to acquire energy consumption models from OEMs. Once provided, sustainable system designs and configurations can be obtained.

3.6 Research gap analysis

3.6.1 Research trends

The sustainability of a manufacturing system is a function of its anatomy. I4.0 and CPS are changing conventional manufacturing starting from the way product and manufacturing system are perceived, and ending with the anatomy of the manufacturing system. As the manufacturing system and its perspective products become virtual models in digital manufacturing, their expected sustainability can be an essential dynamic feature that corresponds to their changes, modifications or configurations.

Demand Response has become a trend when it comes to energy management as can be seen in the recent few years. Scheduling, for example, was customised in many research works to manage DR. However, there is more systematisation when discussing energy flexibility in terms of breaking the consumption down into its main contributors (e.g., TBS, certain production machines, certain services, etc.).

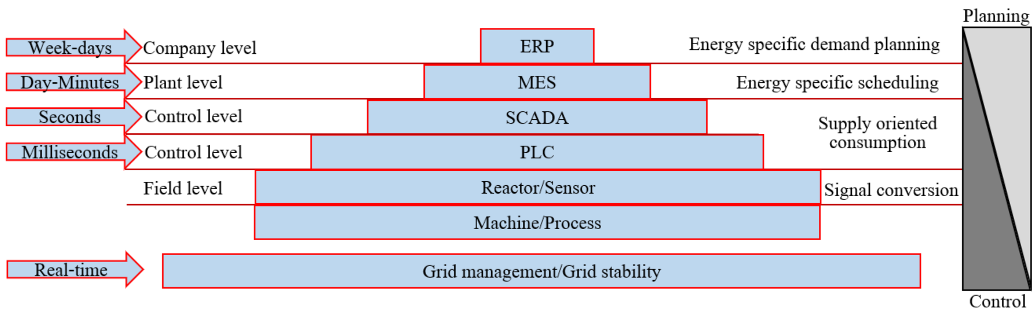


Fig. 3.5: *Industrial automation pyramid and its relation with energy planning and control [Weckmann & Sauer 2019]*

From an automation systems perspective, as depicted in Figure 3.5, PPC activities (at multiple levels) and their planning may meet energy provision/forecasting plans. The period required to make load adjustment ranges from 5 minutes to 5 days [Roesch et al. 2019], or hours to years [Keller et al. 2017]. Thus, the methodology of production/manufacturing planning is changing to adapt to energy prices or energy availability in renewable energy sources.

3.6.2 *Research gaps*

When it comes to load shifting, the majority of the aforementioned research approaches utilised production buffers and manipulated their capacity. In a typical discrete manufacturing industrial scenario, this is enabled by varying the processes' time and speed. Thus, certain "influential" machine component settings are changed. If such changes are to take place in the hardware, they will take significant time. In addition, the new settings era supposed to be valid for a reasonable period of time. For software changes, the effect relies on the control programme structure and its built-in capabilities to be flexible enough. As a result, the planned changes should target the software side and the system should be designed to adapt to such changes. EF literature did not show any of the aforementioned approaches, rather, it still suffers scattering in terms of being case-specific and in the early phase, laying out its theoretical foundation. It is noted that EF literature has specified some EF characteristics and measures to qualify it to design parameters, however, the necessary systems' engineering tools are not yet available to put it into action.

Following the argument above, it becomes logical to search for the most suitable "building unit" that enables the system to interact positively with changes. On one hand, this requires understanding the behaviour of the building unit through energy consumption modelling in order to guarantee that EF management can be achieved across life cycle stages. On the other hand, there should be a system engineering approach in which the prototyping of EF is tested at the design phase. No general architecture or tangible methodologies are structured to define pragmatic system design methods. There is a knowledge gap in EF literature as it aims to deal with the current status of the studied systems rather than building a proactive approach to designing them. This can be interpreted in the lack of life cycle perspectives in the great majority of EF research works. Once designed, it becomes viable to evaluate the degree of flexibility by means of simulation tools that utilise the engineered models.

Strategically, EF models have to contain KPIs to be matched to energy supply sources, and potentially to connect to energy management systems.

Investigating the literature reveals a lack of in-process data investment in general, and for energy flexibility in particular. Acquiring data from the manufacturing system units and embedding their influence in units' models makes these models more interactive in terms of visualising/reporting the performance as a function of the operation parameters. Furthermore, in-process parameters can assist decision-making by either analysing them or editing their value to change the unit's status. For EF, PLCs and other types of industrial controllers can access in-process parameters and modify them which makes controlling EF more precise once energy consumption patterns and requirements are defined.

With the current industrial movement to transform every possible aspect of the industrial environment into a CPS that has both physical and digital/virtual counterparts, it is only a matter of time until EF research takes its first steps on this path. It has been shown earlier that energy management in manufacturing is slowly but surely becoming more integrated with the manufacturing system and its support units. Thus, there is a gap between energy management technologies under I4.0 and the practices of energy flexibility. It is a valid assumption to invest in the same methods and techniques used for energy management under I4.0 for achieving energy flexibility. The progress of this is still limited as it can be noted in this chapter. On the other hand, the potential is quite promising. EF is an advanced implementation of energy management in manufacturing/production where the allowed amount of energy to be consumed is a function of the energy prices/sources. However, comparing EF status to the current status of energy management under I4.0 shows that EF is still lagging behind and much more work inspired by I4.0 advancements can be further introduced. As a concept, all the approaches that are valid for energy management can be harnessed for further application of EF. Technically, some of the current practices of energy management touch on adjusting energy consumption to changing electricity prices, however, a proper systematisation of EF is not included. In return, VRE integration was somehow neglected when studying energy management whereas it is given attention in EF. Genuine related ideas like investing in compressed air energy storage are discussed.

Discussing the investment in I4.0 in more depth, there is a lack of using I4.0 technologies such as big data, IoT and CPS. This lack of connectivity will hinder the use of artificial intelligence techniques and analytics to understand the system's behaviour (or machine, component) behaviour, thereby, enabling the allocation of the best possible flexibilisation approaches. EF has not yet taken full advantage of these technologies. Such adoption of them will have a great impact on:

- the status evaluation of the studied system due to data availability. As a result, the system's behaviour can be better recorded and further association of the parameters can be created.
- enhanced decision-making due to data availability and its processing methods. Data mining methods and artificial intelligence can contribute significantly to behaviour analysis once data are secured by means of the appropriate communication channels.
- a major change in the strategic planning due to the possible in-depth knowledge of the system life cycle. Thus, energy consumption knowledge and control can be stored in the simulation tools to assist the system operator/decision-maker (whether human or machine) in decision making and design validation.

As IoT enables accessibility to the component level, and it has been shown in this chapter how component-based approaches were utilised in machine tools for example to achieve energy sustainability, however no further expansion is found to cover other fields of application or to generalise the proposed models.

As shown earlier, electric drives' energy consumption can be improved and controlled, thus, it can be engaged in EF. With the continuous growth of factories' automation and its spread to cover most of the manufacturing activities, more robotic devices will take part in manufacturing. Furthermore, linking the stations that use various forms of electric drives to the network is easier than before thanks to the advances in ICT. Therefore, the traditional methods of controlling drives' energy consumption (e.g. offline trajectory design) are about to change. Nevertheless, research on EF did not thoroughly investigate this issue, nor introduce a systematic approach to achieving it. The operation of EDs depends on their control programme. Therefore, the authorised access to the control programme means the possibility of customising certain functions/parameters to change the status of energy consumption.

To this end, and in accordance with the research objectives mentioned earlier in 1.2.4, Table 3.5 below summarises the research gaps identified based on the literature review:

Research Gap	Research Objective
The absence of a design methodology that guarantees a proactive energy flexibility design starting from the early design phase of the modern manufacturing system	*Objectives 1 & 3*
The limited engagement of I4.0 technologies in energy flexibility design, implementation and evolution.	*Objectives 1 & 2*
The non-existence of the main building units of a cyber-physical system that are capable of covering the life cycle phases with the ability to report their energy consumption behaviour so that they can enable enhancing energy flexibility.	*Objective 3*

Table 3.5: *Research gaps based on the literature review and their corresponding research objectives*

Chapter summary

This chapter aimed to investigate and identify the research gaps in energy flexibility application by comparing it to manufacturing's energy management practices under I4.0. To evaluate the design status in this field, it was necessary to include a background on the recent changes in manufacturing systems design methodologies and in the I4.0 manufacturing paradigm. Furthermore, the possibility of including electrical drives' energy consumption in EF is discussed. The following conclusions are drawn:

- RMS did not give enough concern to sustainability, whereas under I4.0 technologies, sustainability has been regarded as a design parameter. The concept of component-based design has the potential to support sustainability through the reusability of developed components. Besides, 'I4.0' came into existence which (via RAMI 4.0) is an upgrade to the traditional component-based design methodology. Meanwhile, I4.0 technologies continue to support the same functionalities of RMS.
- A great adoption of I4.0 technologies took place in order to support the management of manufacturing energy consumption. For this purpose, software tools, applications and CPS are being developed assisted by the cloud and AI technologies. On the other hand, the improvement fields targeted when designing energy flexibility suffer from a great lack of I4.0 technologies contribution.
- Most energy flexibility research is focused on discrete manufacturing where manufacturing units' configuration(s) can be changed allowing further "flexibilisation". Works of literature do not indicate precisely the life cycle phase when energy flexibility is integrated with the system. Nevertheless, some indications of the necessity of considering energy/energy flexibility as a design parameter exist.
- The field of machine tools relied on component-based approaches, as rescheduling the machining process requires a considerable lead time. Consequently, rescheduling (i.e. changing the workpieces machining order) would impact productivity. Apart from this, component-based design is not touched on thoroughly.
- The main research gaps to be tackled in this work are declared in Table 3.5.

Chapter 4

Research Methodology

"Il n'est pas certain que tout soit incertain
It is not certain that everything is uncertain"
— **Blaise Pascal**

THis chapter will illustrate the methodology proposed to tackle the research gaps extracted from literature and explained in Chapter 3.

4.1 Analysis of research gaps

The research gaps shown earlier in Table 3.5 are linked with three objectives of this research. The means of achieving these objectives (whether tools, methods, inherited technologies, etc.) are investigated.

In its essence, this work brings energy flexibility from being treated as an isolated entity/problem to a structural characteristic taking into account by manufacturing systems' designers. Unfortunately, as it has been shown in Chapter 3, a "proactive" design methodology is still missing. Although many energy flexibility implementation methods were introduced in the literature, they were "reactive" by nature, as they dealt with a built system. Therefore, it is necessary to have energy flexibility designed "proactively", i.e., in the early design phases. Moreover, when targeting such a proactive design, it makes sense to consider the most up-to-date technologies, which currently are the Industry 4.0 ones. Therefore, these requirements are translated in

Objectives 1 &3 where understanding the behaviour of energy consumptions helps to embed it in the so-called "building units" that describe the assets to be used while creating the manufacturing system.

As the utilisation of Industry 4.0 technologies in manufacturing energy flexibility is limited compared to that in manufacturing energy management, the capabilities Industry 4.0 technologies offer have to be further invested. Therefore, *Objective 2* is focused on a further utilisation of Industry 4.0 technologies. In relation to the subject of this work, this relates to the development of "building units" (by using I4.0 component), the acquisition of energy consumption data (by using IoT) and building the interactivity in them once deployed in a CPS. The ability to interact expresses the change of operation parameters to influence energy consumption, thus, to achieve energy flexibility.

As a result of the previous arguments, meeting the aforementioned objectives can be assessed by technical measurable deliverables (i.e. quantitatively) and built virtual models. The prediction of components' energy consumption requires collecting energy consumption data, then formulating the behaviour of energy consumption in a suitable usable model. Therefore, a corresponding data collection method is constructed. For the delivered virtual models, the assessment is based on the successful data exchange and the possibility to be reused. The intended data collection method and the method of building virtual models will be detailed in the following sections.

As Figure 4.1 shows, the workflow follows four stages: descriptive, predictive, prescriptive and the automation.

Descriptive analysis: The current status of energy management and energy flexibility from an automation perspective and taking into account the transition to I4.0 is analysed. This analysis was introduced in the literature review in Chapter 3 (summarised in 3.3.6 and 3.4.8).

Predictive analysis: With a focus on the component level, the methods of performing predictions of the component's energy consumption behaviour are explored. Then, using some motion control concepts, a method to achieve this is introduced.

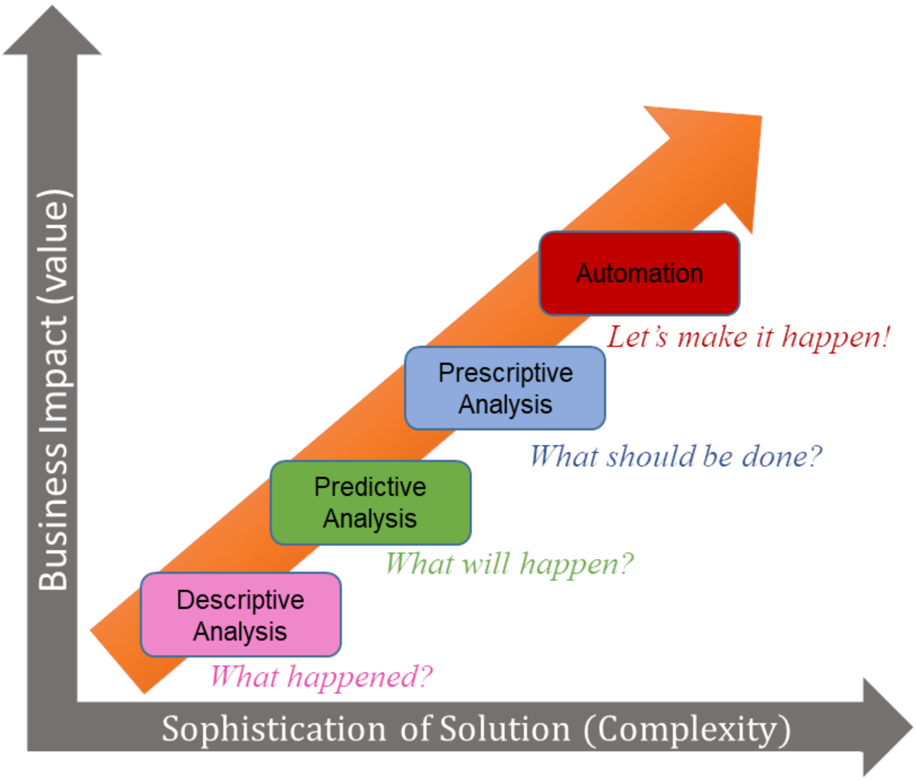


Fig. 4.1: *Analysis types (adapted from Gupta [2017] and modified)*

Prescriptive analysis: The vision of decision-making based on the resultant predictions within a digital manufacturing environment is put forward with its implementation means.

Automation: The solution is put into action by aggregating the previously made conclusions in a mini-scale component to show the applicability of the proposed solution using smart manufacturing technologies.

4.2 Data collection

Energy data are usually obtained by means of energy meters (and smart meters) installed on production machinery. By reporting historical data, a descriptive analysis of energy consumption is produced. Meters send station data, not components' data, otherwise, a huge number of meters are required. As the only reported parameters are electrical ones (e.g., current, power), the influence of in-process parameters (e.g., torque, velocity) on energy consumption is not reported.

Due to the significant energy consumption of electric drives, an electric drive is chosen as an example of the component whose energy consumption is to be studied. Manifesting the engagement of Industry 4.0 technologies in the design of energy flexibility, they will be engaged in data collection, the design of a cyber physical model of the component, and the exchange of data while establishing a real-time connection.

As a general guideline, it is targeted to collect data related to the components' energy consumption. Obtaining these data and synchronising them with the task/process parameters is not straightforward, therefore, it is necessary to understand the possible ways of accessing them, then modelling such a system, and the architecture of communication so that a data collection method can be put into action. Once data are obtained, the best way to model energy consumption, and the make use of the model is investigated. Trajectory design parameters have a strong influence on energy consumption, therefore, the aforementioned aspects are explained in detail in Chapter 5.

In continuation to the previous phase, it is investigated how to contextualise the built models in the life cycle of the manufacturing system, i.e., building energy flexibility in the components of the manufacturing system. An important aspect here is to maintain the reusability of the components, and another is to adapt I4.0 component as theorised in RAMI 4.0.

Collectively, the success here is assessed based on the successful data transfer (logging parameters using IoT an technology), and the ability of the model of energy consumption to give accurate results in addition to the applicability of integrating it in a cyber-physical system. Then, in case an external parameter (i.e., energy availability condition) is externally imposed, motion parameters can be changed to suit the new set-up.

4.3 Component-based design approach (CBDA)

With regards to the system's anatomy, decentralised automation allows the control of the industrial equipment according to the availability of electrical energy [Boehm & Franke 2017]. When designing a production system, the planner has to develop different solutions to support the system's energy flexibility with regards the structural characteristics in particular [Unterberger et al. 2018]. To overcome the challenges faced by automation design for CPS, Seshia et al. [2016] propose to use a set of design features that include a component-based approach as a way of tackling the increasing complexity of CPS and to ensure the reusability.

To comply with I4.0 component concept, its virtual representation shall contain all relevant information related to the physical, functional, and behavioural properties of the represented physical object [Röpke et al. 2016]. Therefore, considering energy consumption as a characteristic that is influenced by the component's physical properties, it is logical to include it in the virtual representation. As mentioned earlier in section 3.1, two design approaches are applicable in smart manufacturing: component-based and model-based. Depending on the intended production/manufacturing planning level, a suitable approach is chosen. For a shop floor device particularly, component-based models should be built and used later when attempting to model the higher levels of manufacturing. This principle is valid for both energy flexibility planning and manufacturing system design, which are expected to be fused in future manufacturing systems. However, not all components can be subjected to load shifting, since only those whose velocity and cycle time can be varied may participate in load shifting and contribute to energy flexibility. Again, this fact stresses the importance of building models whose elements (component models) reflect the flexibility of the system structural architecture.

Creating energy-flexible components is aimed to be consistent with RAMI 4.0 and its corresponding I4.0 component architecture (Figure 4.2). As the chosen component is an electrical drive, it represents a 'Field Device' on the *Hierarchy Levels* axis of

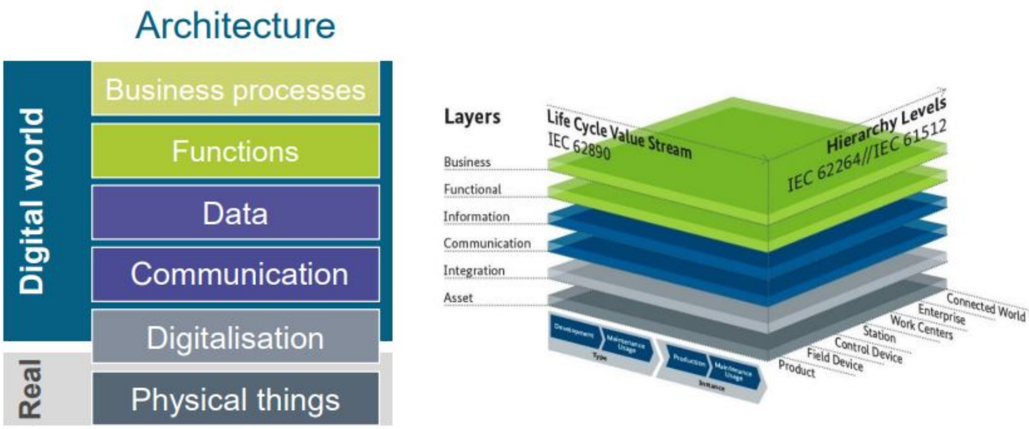


Fig. 4.2: *RAMI4.0 and the architecture of I4.0 component (Plattform Industrie 4.0 [2018])*

RAMI 4.0, and the motion controller/drive with the PLC act as 'Control Devices'.
For the *Layers*, the transition from the 'Real' to 'Digital World' takes place as the 'Communication' is established. After representing the component in a digital format, the 'Integration' involves providing computer-aided control of the technical operation and events generation from the asset. A uniform data format will be used to direct data to the 'Information' layer achieving a successful 'Communication'. In the 'Information' layer, a run time environment and an execution of event-related rules are provided [Adolphs & Epple 2015].
For the 'Life cycle', it is aimed to cover the early design phases. RAMI 4.0 differentiates between the "Instance" and the "Type", with the "Instance" being a unique outcome of the "Type". As such, the focus in this work is on the "Type".

4.4 Research map

In Chapter 5, the energy consumption of electric drivers will be investigated in order to identify a method to embed it in the resultant energy-flexible component (*Research Objective 3*). Then, as it is aimed to create an energy-flexible component, the position of electric drives in the design of manufacturing systems is looked into. Also, by understanding the data transfer in a motion control system, the contribution of IoT in terms of changing trajectory parameters becomes clearer (*Research Objective 2*).

Chapter 6 explains the context of manufacturing system life cycle in which energy flexibility is intended to be embedded through the component-based design approach (*Research Objective 3*). The focus here is on the early design phases and relates to the manufacturing systems engineering (*Research Objective 1*). The capability of virtual engineering is utilised so that a cyber-physical representation of the component is created using the tools available for the author in Automation Systems/WMG.

An empirical validation is conducted in Chapter 7, in which a real application of the aforementioned reflections of the research objective is put into action.

4.5 The novelty of the current work

This research work analyses thoroughly the advancements in manufacturing energy flexibility. Based on the status evaluation, it is aimed to bridge the gap related to the lack of digital technologies utilisation for improved manufacturing energy flexibility. As shown earlier in the literature review chapter (Table 3.2 specifically), digital technologies are heavily invested in manufacturing energy management, but their full potential is not widely taken into account. Another novelty is found in the design of flexible sustainable manufacturing systems. The methodology and implementation focus on the application of CBDA, but from a CPS perspective. On one hand, energy flexibility design is conceptualised in the component design, which is not addressed intensively in literature as shown in Table 3.3. On the other hand, the proposed concept can aid system builders in understanding a component's energy consumption behaviour across its life cycle phases. Furthermore, electrical drives energy consumption is not addressed in energy flexibility literature, despite the significance of its industrial electrical power consumption. Therefore, in addition to the academic value of this work, the industry can benefit from the results of this work in terms of monitoring and predicting their automation equipment's energy consumption in order to increase the potential of energy flexibility.

Chapter summary

The research gaps are analysed in order to identify the means of achieving research objectives. The manufacturing component to be studied and converted into an I4.0 component is specified. Then, the method of collecting the component's energy consumption data and embedding the data in a usable model is explained. Seeking the consistency with RAMI 4.0, the standard architecture of I4.0 component is explored so that building energy-flexible component follows its guidelines. Finally, The points of novelty that characterise the presented work are also highlighted.

Chapter 5

Energy Flexibility Through Motion Control

"Two things control men's nature, instinct and experience."

— Blaise Pascal

As highlighted in the conclusion of the literature review and the research methodology, one of the novelties of this research is to utilise motion control in the implementation of energy flexibility at the component level, on the way to embedding such a capability in the created virtual models. To achieve this, it is necessary to understand energy consumption due to trajectory design in order to find the suitable method of modelling energy consumption data, and the communication architecture of the motion control system, so that configuring motion control parameters becomes possible.

5.1 Energy consumption in trajectory design

5.1.1 Energy consumption as a trajectory design criterion

Trajectory design corresponds to certain application needs such as accurate positioning, reducing residual vibrations and minimising the execution cycle time. In fact, these exemplary requirements constituted the basic research motives and optimisation targets.

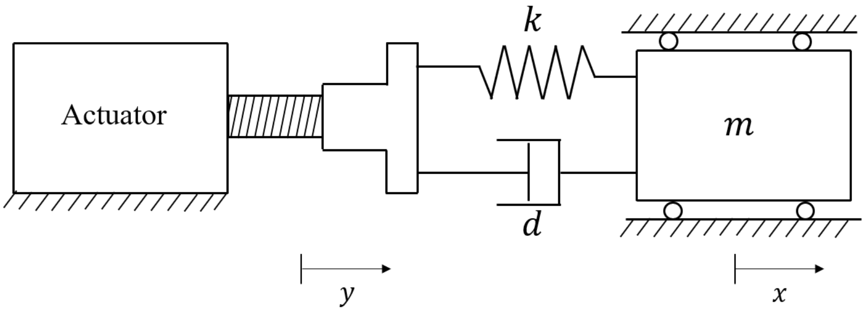
Later on, with the rise in energy prices and the spread of automation applications, the consideration of energy consumption came into the scene and continues up to the moment as sustainability is now a global concern. Energy consumption improvement can be reasonably attributed to the motion smoothness and the jerk bounding design of trajectories [Nguyen et al. 2008]. As explained earlier, the jerk profile corresponds to the change of force(s) acting on the mechanical system. By limiting jerk values and preserving as much smoothness as possible, energy maximum values can be limited and its changes are supposed to be smoother. Collectively, the optimisation criteria can be classified into [Rubio et al. 2012, Assad et al. 2018]:

- Minimisation of the execution time leading to improved productivity.
- Minimisation of the jerk which yields better accuracy and reducing equipment wear (less maintenance cost).
- Minimisation of the consumed energy that is less actuator effort
- Hybrid criteria which can be a combination of the previous targets.

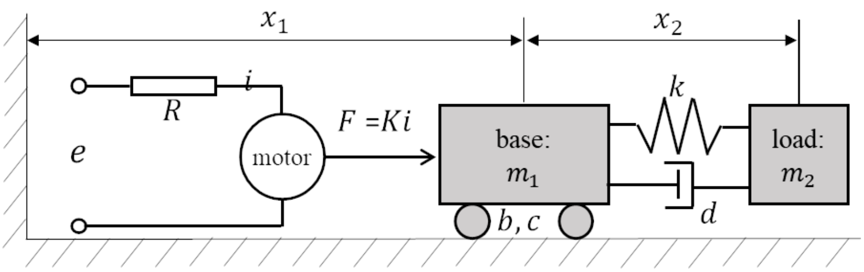
In relation to the hybrid criteria, decreasing energy consumption criterion is accompanied by the vibration reduction. Considering the flexibility in the mechanical structure, the system's damping will cause energy losses in addition to losses caused in the electrical circuit. Therefore, many models that depend on the application (e.g. robotic arm, CNC) are proposed in the literature. In another approach, when hybrid criteria optimisation is conducted, the objective function contains some weight coefficient (e.g., Gasparetto & Zanotto [2010]) to direct the solution to a preferred characteristic of the result.

5.1.2 Systems modelling and Exemplary profiles

A general mechanical system is represented with its mass (m), an elastic spring whose efficient is (k) and a damper (d) as shown in Figure 5.1a. Then y is the input trajectory and x is the system's response. When targeting the resultant energy consumption, various models can be assumed depending on the possibility of solving the assumed model. For example, Figure 5.1b shows the drive with the consideration of the motor factor (K), its current (i) and resistance (R). Also, the friction here is further detailed into b, c.



(a) A linear model with one degree of freedom [Biagiotti & Melchiorri 2008]



(b) The second-order linear flexible structure [Chen et al. 2016]

Fig. 5.1: *Some potential models of the servo-led systems*

In the mechanical system case, the relation between the input and the response is expressed in the equation [Biagiotti & Melchiorri 2008]:

$$m\ddot{x} + c\dot{x} + kx = d\dot{y} + ky$$

Whereas, when including the electrical variables for the system in Figure 5.1b, this becomes [Chen et al. 2016]:

$$Ki(t) = (m_1 + m_2)\ddot{x}_1(t) + m_2\ddot{x}_2(t) + b\dot{x}_1(t) + c$$

Then, the total energy consumption (for the system in Figure 5.1b specifically) is

[Chen et al. 2016]:

$$EC = \int \Big(R i^2(t) + K \dot{x}_1(t) i(t) \Big) dt$$

As it can be seen, the energy demand in applications that rely on electrical servo drives is strongly influenced by the applied trajectory profiles, however, the servo drive components are responsible for other energy losses [Hansen et al. 2014]. Due to their mathematical continuity until their second derivative (C^2 steady), and based on the fact that both the optimal execution time and the trajectory profile have a direct impact on the energy consumption, Hansen et al. [2014] discussed three types of trajectory profiles as potential candidates: trapezoidal acceleration profile, sinusoidal profile and polynomial profile (degree 5). Conducting this study by means of simulation required assuming some mechanical properties such as the system's inertia, Coulomb friction and viscous damping.

Additionally, parametric curves can be used for energy consumption control. Shi et al. [2018] used quintic NURBS profile to guarantee the continuity of the jerk profile and make the profile flexible and easy to modify. Next, a multi-objective particle swarm optimisation algorithm is used with the objectives of minimum energy consumption and the smoothness of the curves.

5.2 Towards energy flexibility

To understand the mechanism by which the energy consumption of electrical drives can help in achieving energy flexibility, the architecture of the motion control system has to be clarified in addition to the possible data transfer means.

5.2.1 The architecture of motion control system

A motion control system (Figure 5.2) is composed of the following [Gürocak 2015]:

- Human–machine interface (HMI),
- Motion controller
- Drives

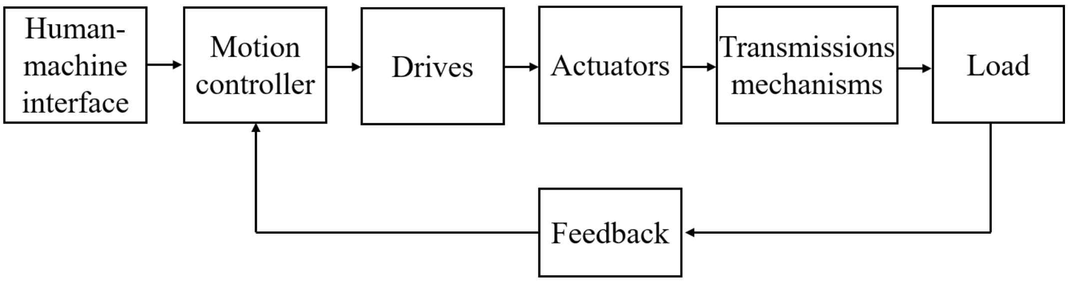


***Fig. 5.2:** Components of a motion control system [Gürocak 2015]*

- Actuators
- Transmission mechanisms
- Feedback.

The motion controller is responsible for generating motion profiles, monitoring the input/output and closing the feedback loops. Once the command signals are generated by the controller, the drive amplifies them to high-power voltage and current levels that are necessary to operate the motor. As indicated by Gürocak [2015], the most recent drives often integrate the functionality of motion controllers, with the embedded capability to perform complex motion-control functions. AC drives, for example, are complex devices containing power electronics that are a converter, a DC link and an inverter. The speed of the motor is varied by setting the frequency and voltage of the three-phase sinusoidal waveforms provided to the motor. It should be noted that AC drives are considered complex [Pease et al. 2018] as they contain a lot of power electronics to modify the input wave.

Actuators can be electromechanical or hydraulic devices that provide the energy needed to move the load in accordance with the received commands. Meanwhile, feedback devices (e.g., tachometers, encoders, etc.) transfer the measurements of load speed, velocity and current to the control units to close the loop and trigger the corresponding commands based on the control algorithms.

5.2.2 *Communication and data transfer*

Several communication protocols are used to allow industrial devices to 'speak' to each other successfully, e.g., EtherCAT, Modbus, Profinet, etc. These modern communication protocols are forms of Fieldbus, which constituted a milestone in drives' communication. Before the introduction of Fieldbuses, drive systems typically had analogue interfaces which used I/O terminals to transfer control commands to the frequency converter. Fieldbus enabled distributed I/O signals to be integrated into the control system using cyclic communication [PNO 2012].

In a Fieldbus-based system, the drive is able to achieve closed-loop servo control via bidirectional communication in which the drive and motion controller exchange data and feedback messages [Hu et al. 2008]. As this feedback includes torque and force, in addition to many other data, Fieldbus technology promises to promote efficiency [Hu et al. 2008]. As explained earlier, the velocity and acceleration are directly influenced by the voltage and current which, in turn, can indicate the amount of the consumed electrical power. It has been shown earlier in the literature review (Chapter 3) that these data have not been invested in energy management as yet. Due to the revolution caused by Fieldbus as a communication technology, it can be expected that IoT can help to further exploit these data.

With the current international trend in the last decade to shift to sustainable manufacturing, industrial vendors are started developing communications protocols to support the industry in achieving this. For example, PROFIenergy (which is a part of Profinet) is intended to help in energy management and efficiency optimisation [PNO 2012]. Nevertheless, as long as there is no unified communication protocol for energy, the currently available IoT ones should continue to be investigated until a major change takes place.

5.2.3 *Manufacturing System's anatomy and architecture*

The discipline of manufacturing systems design borrowed a lot of terminology from computer science due to the increased involvement of informatics-based systems in machine design. Examples of this include open-architecture, modularity, connectivity, availability, expandability and portability [Wright 1995]. Even the term "component-based" originates from software engineering. Now, as I4.0 is based not only on information technology but also on communication technology, it can be expected that a lot of communication concepts will be involved.

In motion control, one main advantage of using 'components' is their capability to support interoperation among software modules [Hu et al. 2008], in addition to the reusability when integrated into different reconfigurations. To investigate such advantages in leveraging the system's sustainability for motion control applications specifically, the state and values of in-process parameters should be transparent and communicable. To move towards achieving energy consumption, it first has to be modelled. Then, it is adjusted in accordance with the pre-specified measures. In this context, Sinnemann et al. [2020] indicate that users can build and develop their own models of components energy consumption, however, these will typically not be as accurate as those provided by the manufacturer due to the lack of internal parameters knowledge.

Therefore, the use of motion drives components should be further developed to account for energy consumption behaviour, and in a way that facilitates its utilisation in manufacturing system/process design.

5.2.4 Proposing application approaches

In a smart manufacturing environment, the availability of data grants new opportunities for solving conventional industrial problems. Although a lot of work has been done on trajectory design for improved energy consumption, there is the opportunity to use machine learning and advanced statistical tools in energy consumption prediction, as a beginning, and then to equip the system with the appropriate tools for energy flexibility decision-making.

Literature on electrical drives in smart manufacturing is limited, especially when it comes to including energy consumption related machine learning techniques. For example, Adenuga et al. [2020] used logistic regression analysis to predict the cost of energy and the efficient energy demand. Also,[Zhang & Yan 2021] proposed the use of data-driven optimisation to improve industrial robot energy consumption. Artificial Neural Networks were used to identify the relationship between operating parameters and energy consumption.

Hence, two approaches are possible to achieve energy flexibility through trajectory design:

- One profile design: by parametrising a specific motion profile so that it is possible to modify the motion by changing certain parameters. For this profile, its parameters can be linked with its energy consumption.
- Multiple profiles design: where a 'library' of motion profiles is available, and the one that corresponds to the energy consumption requirements can be selected.

Considering the complexity of the electrical drive itself and the great variety of mechanical systems connected to it, machine learning can simplify the process of energy consumption prediction. In the empirical validation (Chapter 7), the possibility of achieving these proposals will be investigated.

5.2.5 Modelling using machine learning

Machine learning (ML) has changed the way data are treated for the purpose of building models (programmes, codes equivalently) [Lee 2019]. As shown in Figure 5.3, data is harmonised with the output so that the model is produced accurately, whereas, traditional programming relied on the parameters of the model to get the required output. To this end, as manufacturing data are abundant, they can aid the modelling process once secured properly. For this purpose, data of energy consumption due to drive's motion was collected and investigated in order to produce the corresponding model by using ML.

ML has the following types [Mattmann 2020]:

- Supervised learning: labelled data are used as a training dataset to develop the

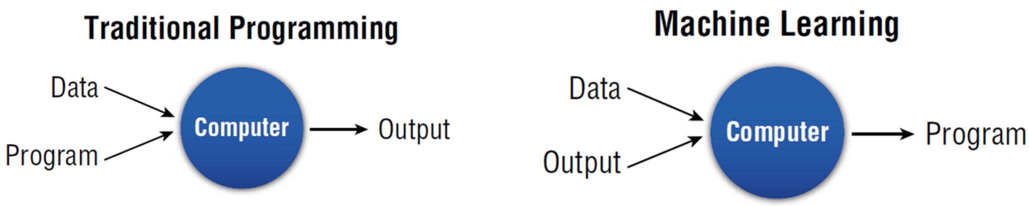


Fig. 5.3: *Machine Learning vs. Traditional Programming [Lee 2019]*

model. Thus, a cost function describes the difference between the predicted and actual values, and the cost is minimised in order to increase the accuracy of the model. *Regression* and *Classification* are supervised learning algorithms where the former deals with continuous values (e.g. salary, age ... etc.), while the latter deals with discrete values (e.g. male/female, true/false etc.).

- Unsupervised learning: it is the process of modelling unlabelled data in order to find patterns or structures. *Clustering* and *Dimensionality Reduction* are the most effective methods to obtain inferences from data alone.
- Reinforcement learning: in this type of ML, the learning system receives feedback on its actions from the environment. Consequently, conclusions about the most favourable results are obtained.
- Meta-learning: a relatively recent area of ML in which the procedure of conducting ML is automated. As a result, an automatic system performs the steps of picking the model, training it and evaluating its outcome.

In this work, a supervised learning technique is utilised in order to predict the drive's energy consumption based on the motion characteristics. Therefore, the methods of Multiple Linear Regression (MLR), and Neural Networks are explained, with their results introduced, in the following sub-sections.

5.2.6 Multiple Linear Regression

The general model of linear regression with k regressor variables after number n of observations (x_{i1}, x_{i2}, ..., x_{ik}, y_i), where i=1,2,...,n is [Montgomery & Runger 2010]:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_1 x_{i2} + ... + \beta_k x_{ik} + \epsilon_i \qquad i = 1, 2, ..., n \tag{5–1}$$

ϵ is a vector of random errors, and β is a vector of regression coefficients. The model can be written in the matrix form as:

$$y = X\beta + \epsilon \tag{5–2}$$

where:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \dots & x_{2k} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{n1} & x_{n2} & x_{n3} & x_{nk} \end{bmatrix} \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} \epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

To minimise the error ϵ using the least square as stated in Montgomery & Runger [2010], the loss function L is:

$$L = \sum_{i=1}^{n} \epsilon_i^2 = (y - X\beta)^T (y - X\beta)$$

To find the least square estimator $\hat{\beta}$:

$$\frac{\partial L}{\partial \beta} = 0$$

and this yields:

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

Next, the predicted output $\hat{y}_i$ is calculated using the equation:

$$\hat{y}_i = \hat{\beta}_0 + \sum_{j=1}^{k} \hat{\beta}_j x_{ij} \quad i = 1, 2, ..., n \tag{5–3}$$

or in its equivalent matrix form:

$$\hat{y} = X\hat{\beta} \tag{5–4}$$

5.2.7 Deep Learning

The implementation of MLR does not allow a lot of flexibility in terms of solution improvement. Whereas Deep Learning gives further improvement opportunities. A deep learning neural networks model has the exemplary structure illustrated in Figure 5.4 which comprises: an input layer, hidden layers and an output layer. Each layer is composed of a number of neurons (units) that are activated/deactivated using an activation function. Thus, by varying the number of layers, the number of neurons in each layer, or the activation function (explained below), solution quality can be improved.

There are many functions that can be used as activation functions such as step function, Sigmoid function, tanh function and Rectified Linear Unit (ReLU). Classically, the Sigmoid function is used where its equation and its derivative are respectively:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

$$\sigma'(x) = \sigma(x)(1 - \sigma(x))$$

If using Sigmoid function, the output of the unit(o) is given as (Figure 5.5):

$$o = \sigma(\sum_{i=0}^{n} w_i x_i)$$

where:

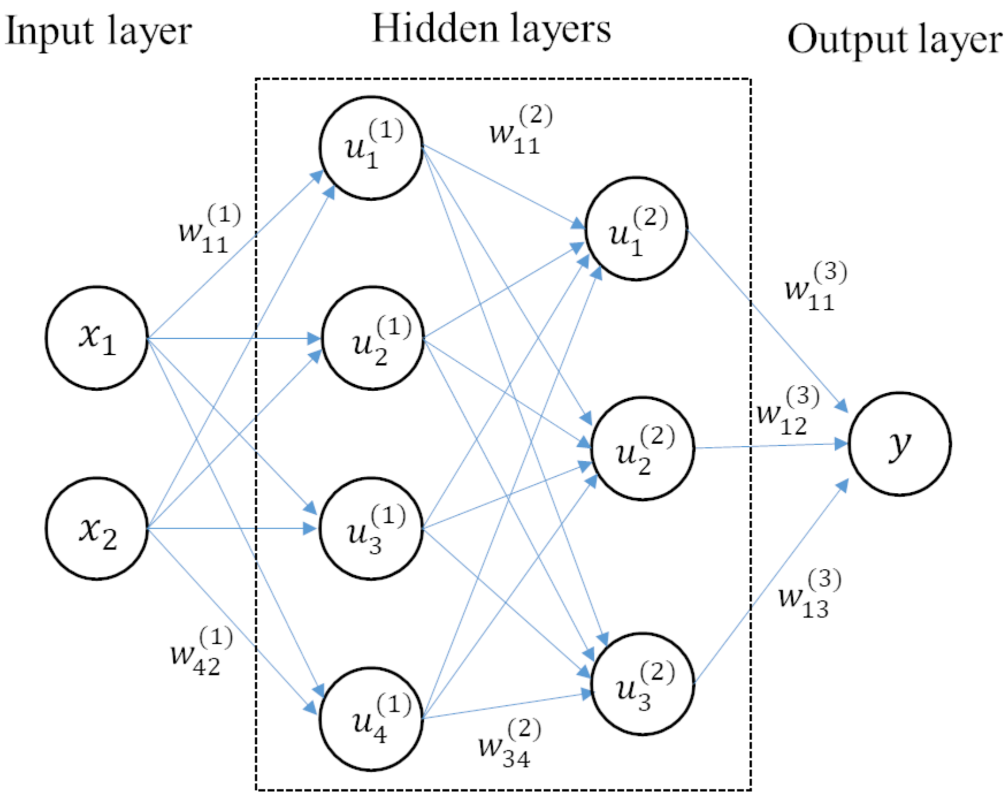


***Fig. 5.4:** Neural Networks model*

w_0 is the unit threshold (bias).

$x_1, x_2, \dots, x_n$ are the unit inputs.

$w_1, w_2, \dots, w_n$ are the interconnection weights and can be expressed as components of the vector $\vec{w}$.

To train the network, the error function to be minimised by modifying the weights is [Mitchell 1997]:

$$E_d(\vec{w}) = \frac{1}{2} \sum_{k \in outputs} (t_k - o_k)^2$$

where:

k is the set of output units in the network.

t_k is the target output of unit k for the training example d.

o_k is the current output of unit k for the training example d.

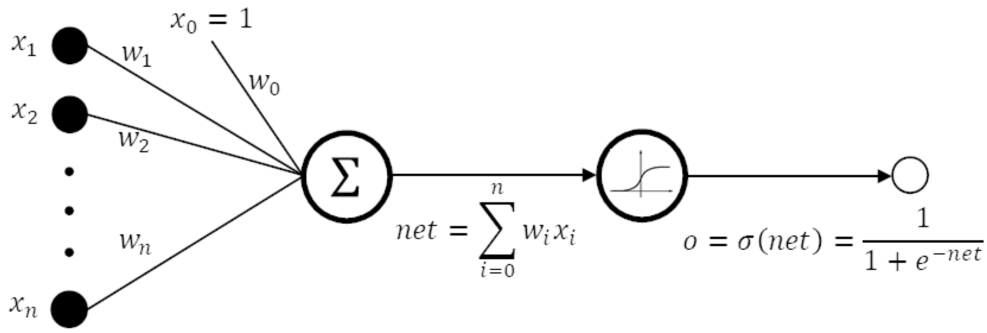


Fig. 5.5: *The Sigmoid threshold unit [Mitchell 1997]*

As E_d expresses the error, the stochastic gradient decent can be used to minimise E_d by updating the weights using the rule:

$$\Delta w_{ji} = -\eta \frac{\partial E_d}{\partial w_{ji}}$$

$$w_{ji-new} = w_{ji-old} + \Delta w_{ji}$$

w_{ji} denotes the weight associated with the ith input to unit j, and the term $\partial E_d / \partial w_{ji}$ resembles the contribution of the weight w_{ji} to the global error. Thus, using the chain rule to update all the weights in the network we obtain [Mitchell 1997]:

- For a neuron in the output layer:

$$\Delta w_{ji} = -\eta \frac{\partial E_d}{\partial w_{ji}} = \eta(t_j - o_j)o_j(1 - oj)x_{ji}$$

- For a neuron in the inner layer:

$$\delta_j = -\frac{\partial E_d}{\partial net_j} = o_j(1 - o_j) \sum_{k \in downstream(j)} \delta_k w_{kj}$$

$$\Delta w_{ji} = \eta \delta_j x_{ji}$$

where:

x_{ji} is the ith input to unit j.

$net_j = \sum_i w_{ji} x_{ji}$ is the weighted sum of inputs to unit j.

Deep learning is implementable using multiple programming languages and platforms. Most commonly, its Python libraries such as Tensorflow (with Keras) and PyTorch are utilised due to the great customisability of the created networks and the ability to use various loss and activation functions.

Chapter summary

Modelling the behaviour of energy consumption of the component is an enabler of embedding energy flexibility in the design of the component. As the chosen component is an electric drive, it is essential to identify a suitable method of its energy consumption in the context of manufacturing systems building. Therefore, this chapter contributes to *Research Objective 3* through modelling the behaviour of energy consumption, and to *Research Objective 2* by understating the contribution of IoT through modifying trajectory design parameters.

The influence of trajectory design parameters on electrical drives' energy consumption is investigated. It has been shown that building analytical models of energy consumption is demanding in terms of the supplement of a great number of electrical and mechanical properties. Therefore, machine learning models are a better choice. Besides, such models can benefit from the data available in smart manufacturing environments. On the other hand, the communication structure is studied to understand the possible channels of data transfer, so that the inputs and output of energy consumption models can be provided and transferred.

Due to the required material properties for both the mechanical and electrical elements in the motion control system such as stiffness, resistance ... etc. , using analytical models to evaluate energy consumption is not the approach to be followed in this work. Instead, machine learning methods such as multiple linear regression and deep learning will be utilised.

Chapter 6

A Life Cycle Perspective of Energy Flexibility in Smart Manufacturing

"The power of a man's virtue should not be measured by his special efforts, but by his ordinary doing."

— **Blaise Pascal**

THis chapter starts by examining the current possible approaches for energy sustainability design in assembly automation systems. Then, the proposed strategy of enabling energy flexibility design in the early phases of the system's design is put forward.

6.1 Energy flexibility strategy for automation systems

6.1.1 Design methodologies and tools of CPS

The basic understanding of CPS design can be expressed as establishing the communication between the elements of the cyber system and the ones in the physical system using suitable communication networks. Physical manufacturing resources can be sensors, actuators, etc., whereas cyber services can be for logistics, maintenance, etc. Communication networks bridge both to allow an effective transfer of data and information.

For CPS design tools specifically, it can be noted that simulation continues to be the ultimate design tool, as it allows understanding of the system's behaviour before being built and also whilst being in operated [Tilbury 2019]. Another benefit is the ability to use some hardware tools to validate the control code in an emulation mode. Tilbury [2019] classifies simulation into the following types:

- Simulation models for manufacturing systems: This type includes two subcategories that are discrete-event simulation and continuous-process simulation.
- Extracting data from the plant floor: Linking the data generated by the shop floor (particularly low-level components, e.g., sensors and actuators) using suitable communication protocols to analyse the performance.
- Virtual fusion and digital twins: Once real-time data is communicated to the simulation model, it becomes possible to conduct multiple reconfiguration scenarios and validate them.

Currently, there is no integrated toolchain that provides the requirements of automation systems design and implementation starting from the prototype to the final functional system [Harrison et al. 2016]. However, in this context, there are high expectations for the impact of OPC UA and AutomationML (or their combination) [Harrison et al. 2016, Monostori et al. 2016]. This potential stems from the increased ability of managing data, its models, their transferability and the possible future utilisation. Components' data include the engineering data such as self-description, and run-time data such as sensor data collected through the communication protocols (e.g. OPC UA and Profinet) [Monostori et al. 2016]. It should be noted that energy consumption as a design parameter does not have a strong representation in CPS design, as yet. Nevertheless, Harrison et al. [2006] highlight the possibility of including energy data in the data model of CPS's component for futuristic design refinements. Therefore, progressing to achieve energy flexibility needs further system engineering effort.

6.1.2 The interaction of energy demands with automation systems structure

In automation systems, energy saving strategies are classified into [Carabin et al. 2017]:

- Hardware solutions: these solutions are based on light design methodologies, energy recovery and energy distribution systems.
- Software solutions: such solutions are applicable in packaging and assembly and they rely on electrical drives operation and control.
- Mixed solutions: they consider a combination of the aforementioned solutions.

The traditional energy monitoring and data collection methods provided by Shrouf & Miragliotta [2015] include utility meters that produce low quality timeliness data. For forecasting the energy consumption, those traditional methods suffer the lack of accuracy and long interval times between readings (e.g., each week). Therefore, IoT devices are preferred as they can be linked directly to the management system.

It has been shown previously, in Figure 3.5, that a conceptual understanding of the relationship between energy planning and control, and the automation system structure can be shaped. In addition, Körner et al. [2019] take DR into account and propose extending the automation pyramid so that it further includes the functional levels of energy supply, grid and commerce (Figure 6.1). Once done, manufacturing activities could follow the same rhythm as the energy market. However, such behaviour of manufacturing/production system is not achievable unless the system possesses the necessary mechanisms, especially with regards to ICT enabled capabilities. In Industry 4.0 terms, this means that in the same way that manufacturing can be distributed, energy is as well. As a result, energy consumption and supply should take the form of shareable data models so that they can become controllable design parameters.

For future CPSs, it is aimed to have "Zero Engineering" during run-time [Foehr et al. 2017]. This should apply to energy flexibility as a design parameter. Therefore, when designing the manufacturing system in accordance with a CPS engineering philosophy, it should be able to interact with the 'available energy' as a resource, and correspond to that quickly and efficiently with the least amount of both hardware and

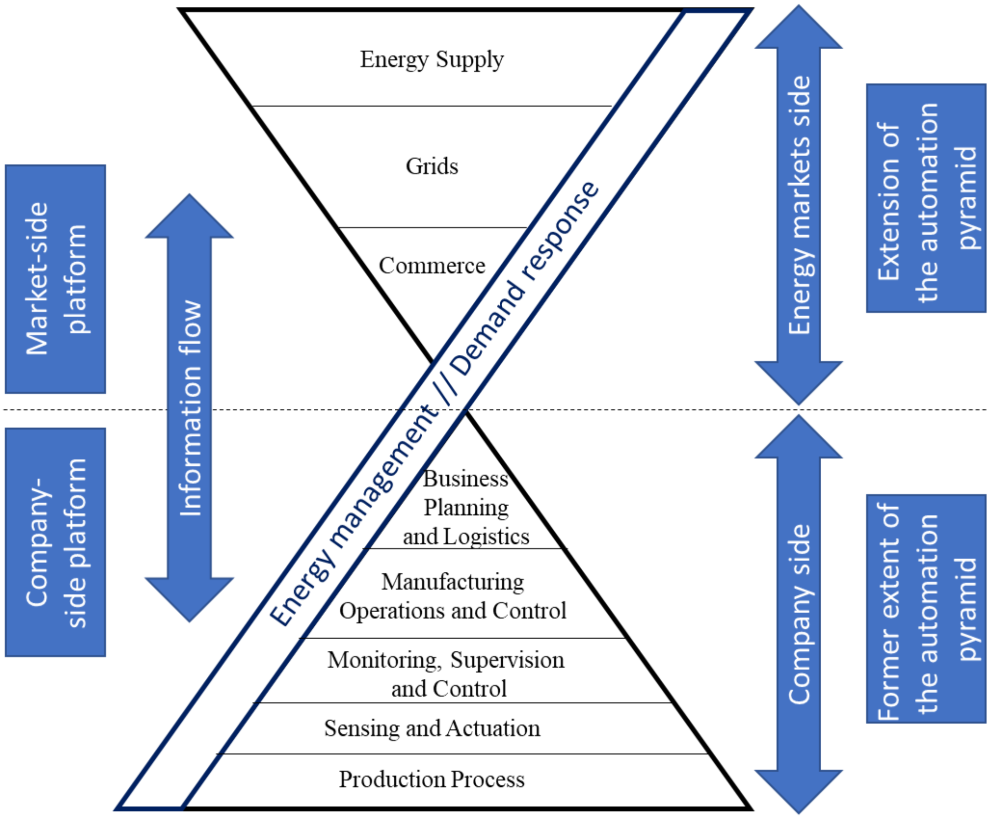


Fig. 6.1: *Linking the company side and the energy markets side for a well-functioning energy management, i.e. DR. [Körner et al. 2019]*

software changes. To guarantee this, the 'information flow' has to be secured, and the data to be communicated should be formatted in an interpretable language for all the levels. Meanwhile, manufacturing systems contain dynamical systems, and Monostori et al. [2016] refer to the identification and prediction of dynamic systems as one of the challenges that face CPS research.

Referring to control levels considered in manufacturing energy flexibility (Table 3.3), a mapping can be established between the control level and the simulation type where discrete event simulation can be utilised for production scheduling, planning and control, whereas digital twins can represent accurately components' behaviour. It was pointed earlier (in 3.1.1) that the level of granularity should be carefully chosen so that it achieves a balance between complexity and functionality. The same principle applies when identifying the level of energy flexibility, e.g., whether at PPC, scheduling or, component level. From a system complexity analysis perspective, system granularity can be defined as "the varying levels of detail of a system, be it a product, a manufacturing system or an enterprise" [Samy et al. 2015].

6.1.3 Integrating energy flexibility in life cycle

For manufacturing systems' builders, there are a lot of functions to be verified while building the system. The current simulation tools typically allow the creation of separate models of the system's /process's control logic, structure, etc. The ideal representation of all these functions can be obtained by building the digital twin.

The digital twin can include 3D virtual geometry models, 2D plane layout models, 3D layout models, equipment state (normal use, maintenance and operation, energy consumption, etc.), real-time physical operational parameters (speed, wear, force, temperature, etc.), in addition to other logical relation elements [Wang & Luo 2021]. As a result, the digital twin of a unit may possess all the necessary information that enables decision-making in relation to energy consumption control (as inputs). However, the necessary algorithms have to be built inside it or to be fed by the orders/signals to trigger the required actions.

To this end, to enable embedding energy flexibility in the system's building units, the designer/builder has to equip the digital twin with two main elements:

- Energy consumption behaviour model: including the ability to predict energy consumption.
- Decision-making algorithm that can identify the best setting of the unit to meet the required amount of energy consumption.

Such intended dynamic behaviour would not be implementable unless real-time data are provided within a smart manufacturing environment. In addition, the timeliness of the decision can be improved if cloud applications are involved and full advantage of its computational capabilities is taken.

6.2 Virtual engineering to support sustainability

6.2.1 Virtual models of manufacturing system's unit

Virtual engineering has received significant attention as an approach for boosting productivity and competitiveness [Ahmad 2014]. Currently, VE takes an important role in the build and engineering of CPS [Harrison et al. 2016]. From a system's design perspective,VE can address the factory level and the lower-level machine-related activities [Cecil & Kanchanapiboon 2007] in addition to the component level ([Ahmad 2014, Ahmad et al. 2018]).

VE offers great flexibility shown in the various levels of granularity associated with a variety of design fields (e.g. mechanical, electrical and control), which yields a significant potential for improvement particularly in the early design phases [Assad et al. 2021]. Virtual models produced by VE tools should exhibit the following characteristics [Cecil & Kanchanapiboon 2007, Assad et al. 2021]:

- Appearance characteristics: to accurately represent the geometry and the appearance of the targeted part, system or environment.
- Simulation characteristics: to simulate engineering behaviour in relation to real-time responses.
- Representation criteria: to have their representation digitalised or in a readable computer format.
- Interface criteria: to interface to Virtual Reality (VR) technology and graphics including supporting semi-immersive/immersive applications.

6.2.2 Supporting sustainable manufacturing through VE

A variety of VE-related tools, technologies and methods can contribute to achieving sustainable manufacturing across different life cycle phases. A framework is introduced by the author to achieve this and it is demonstrated in Figure 6.2.

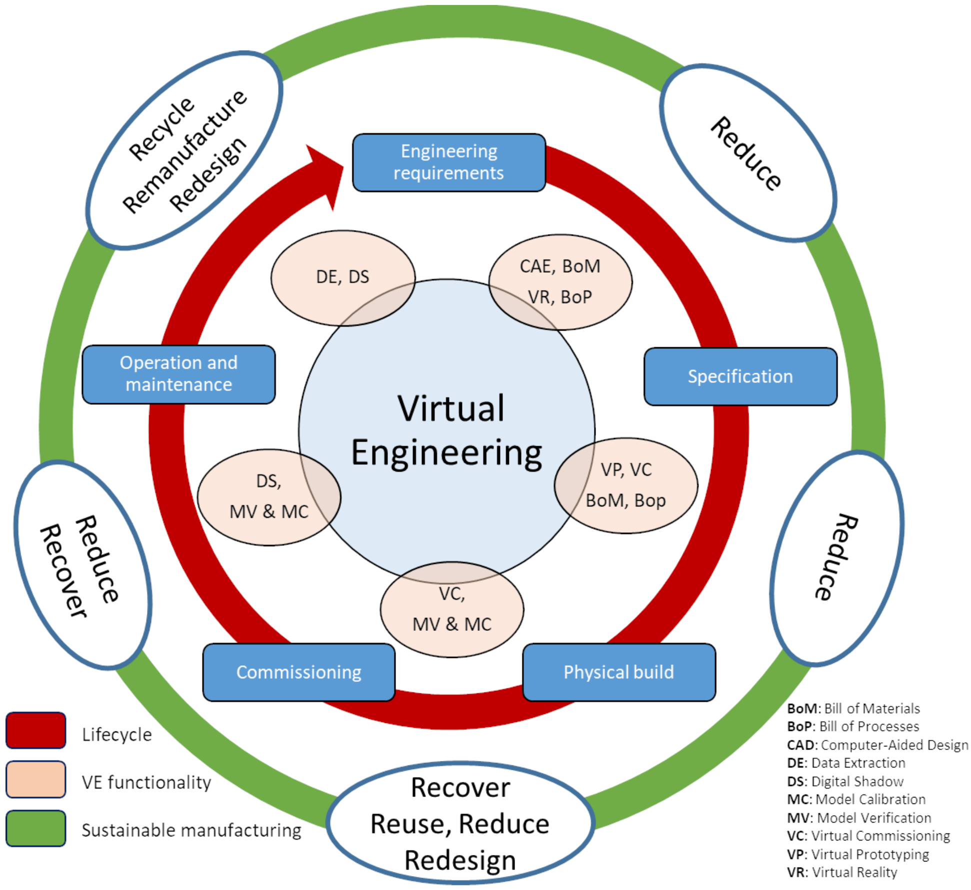


Fig. 6.2: *Virtual Engineering in support of Sustainable Manufacturing [Assad et al. 2021]*

This lifecycle extends from the early design phases, through requirements specifications, physical build, commissioning, operation and maintenance, and ultimately to potential reconfiguration/reuse. As recognised by Assad et al. [2021], VE-relevant tools and ICT-enabled engineering methods, can be used to support the realisation of sustainable design; supporting some of the sustainability 6Rs. The identified tools and ICT-enabled methods are Computer-Aided Engineering (CAE), Bill of Materials (eBoM), Bill of Processes (eBoP), Virtual Reality (VR), Virtual Prototyping (VP), Virtual Commissioning (VC), Model Calibration (MC) and Model Verification (MV). The supported Rs here are [Assad et al. 2021]:

- *Reduce*: it includes the reduction of energy consumption, raw materials, effort, time and the system's complexity.

- *Reuse*: it refers to the reuse of tools, models, designs or the materials used earlier at another phase.
- *Recover*: it can be related to the machine's health conditions e.g. vibrations and energy consumption.
- *Redesign*: it is related to redesigning the processes e.g. changing the operation parameters, and the suitability of the processes/ components to the manufactured product.

Given the aforementioned capabilities and potential improvements, VE tools can be further utilised to support energy flexibility starting from the early design phases. In addition, the live interaction with real-time collected data will extend the capabilities of built virtual models in support of sustainability targets, for example, by using artificial intelligence and optimisations algorithms. The following section will show the vision for reaching this outcome.

6.3 Energy-flexible component design

6.3.1 Categorisation of components

According to [Assad et al. 2019, Ahmad et al. 2015],], the energy consumption of manufacturing components over the time period of its operation can be classified into variable and constant (Figure 6.3).

The energy consumed by constant energy consumers have two sub-categories that are:

- *Base* (E_B): the amount of energy consumed over the system's time of operation t (e.g. PLC power supply), and it is a function of it.
- *Idle* (E_I): the amount of energy lost at the component's idle state, and typically is a function of the drive's efficiency (η).

For the variable energy consumption, it falls under two sub-categories:

- *Ready* (E_R): it is typically noticed in the moving-only components (e.g. gantry), where energy consumption is affected by the velocity (v).

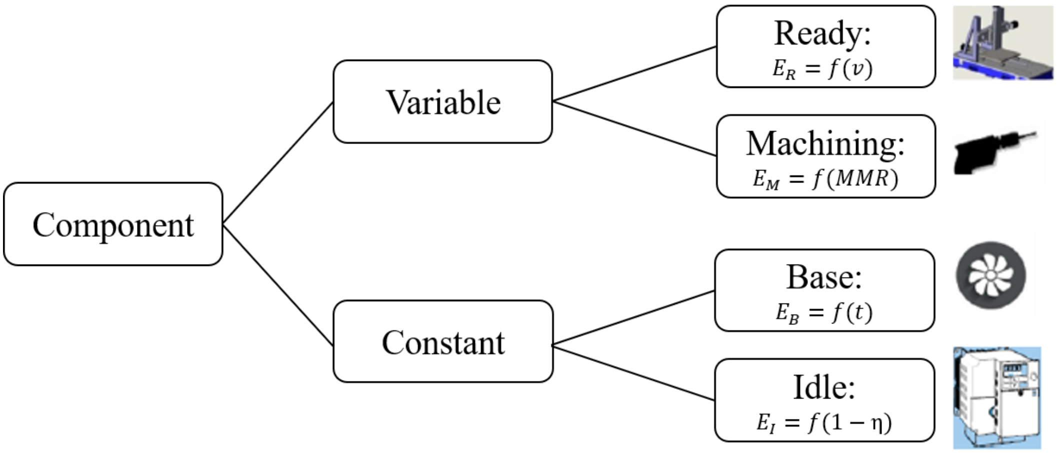


Fig. 6.3: *Components classification in terms of their energy consumption [Ahmad et al. 2015]*

- *Machining* (E_M): it represents the energy consumed by machining devices (e.g. drills), where the consumed energy is a function of the material removal rate (MMR).

This breakdown of the component's energy consumption helps to evaluate its current possible contribution to energy flexibilisation in addition to the possibility of modelling energy consumption as a function of the operation conditions.

6.3.2 *The process of building energy-flexible component*

Based on the aforementioned understanding of the component's energy consumption, a procedure is proposed to build energy-flexible components in a virtual engineering environment, and is shown in Figure 6.4.

VE models are characterised by the visualisation element in the form of 3D simulation which allows the user further insight into the process sequence. Therefore, the initial step is to *create the CAD model* of the component. As the component is a part of a system/subsystem, it is necessary to *identify component connections* especially those the component will exchange data with. The PLC is of particular importance as it is not only the source of control signals, but also the node that data pass through to be communicated to the desired destinations. To be ready for potential future changes in the process, the designer should *identify the task constraints* so that

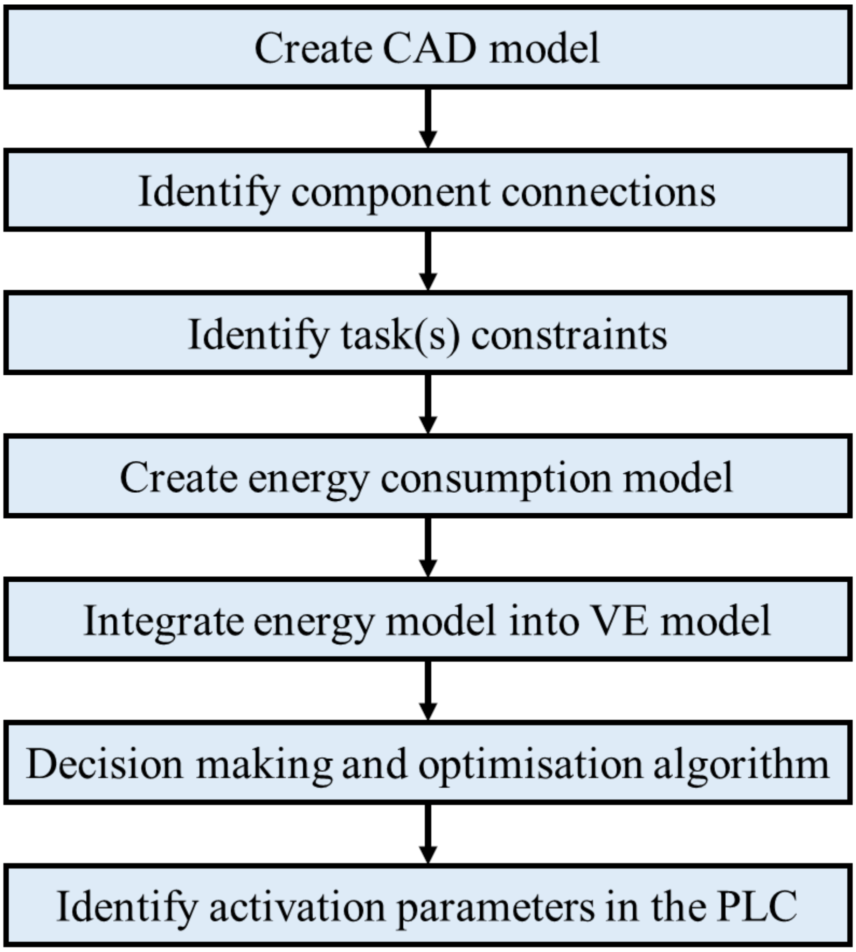


Fig. 6.4: *The procedure of developing energy-flexible component*

they can be linked to the parameters influencing energy consumption, and thus also energy flexibility. For example, maximum velocity and maximum acceleration.

To make the best of the built model, the designer has to *create an energy consumption model*. The model can be analytical in cases where the relationship between the process parameters and the energy consumption is obtainable, or it can be in the form of a machine learning algorithm. Due to the complexity and variability of the manufacturing process, the former is not always implementable. Consequently, the latter option is often more applicable. Furthermore, the abundance of data in smart manufacturing environments makes it a viable choice. The next step which is to establish a way to *integrate the energy model into the VE model*. Although the scientific literature exhibits many successful attempts to utilise machine learning algorithms in the digital twin, there is no standard approach to achieving this. However, a major requirement is to guarantee to feed the virtual model (DT) with the necessary inputs.

To reach the optimal goal of automating the process, a *decision-making and optimisation algorithm* has to be programmed. Such an algorithm can either be internal, on the digital twin platform, or external, on a cloud application for example. The choice relates to the sophistication of the models, the amount of the involved parameters, the quality of the solution, and the time-window the outcome has to be obtained within. The outcome of the decision-making algorithm becomes useful once it is translated into a control signal that triggers an action or a series of actions. Hence, the designer has to *identify activation parameters in the PLC* programme.

6.3.3 Compliance with Industry 4.0

As explained by Lüder et al. [2017], Brecher et al. [2021], the evaluation of a component's compliance with I4.0 takes place with reference to RAMI 4.0 across the three axes, Life Cycle, Layer, and Hierarchy Level.

As virtual engineering models can be developed to digital twins once the communication to the physical asset is provided, the outcome of the proposed method (Figure 6.4) should contain the information required at the layers: *Asset, Integration, Communication, Information, Function, and Business*. Moreover, the coverage of life cycle phases is intended as explained in Figure 6.2.

Referring to Figure 4.2, where the architecture of I4.0 is illustrated, the introduced procedure aims to achieve a transition from the physical thing (asset) - the real world to the digital one by creating the VE model of the electric drive. For the "Communication" aspect, component's connections are identified in order to achieve a successful exchange of data. The "Data" included here are motion constraints, e.g., the minimum and maximum position. In relation to the "Functions", they are limited to the motion controlled by the parameter coming from the PLC as signals and the prediction of energy consumption.

It should be noted that the "Business Process" is not covered in this work.

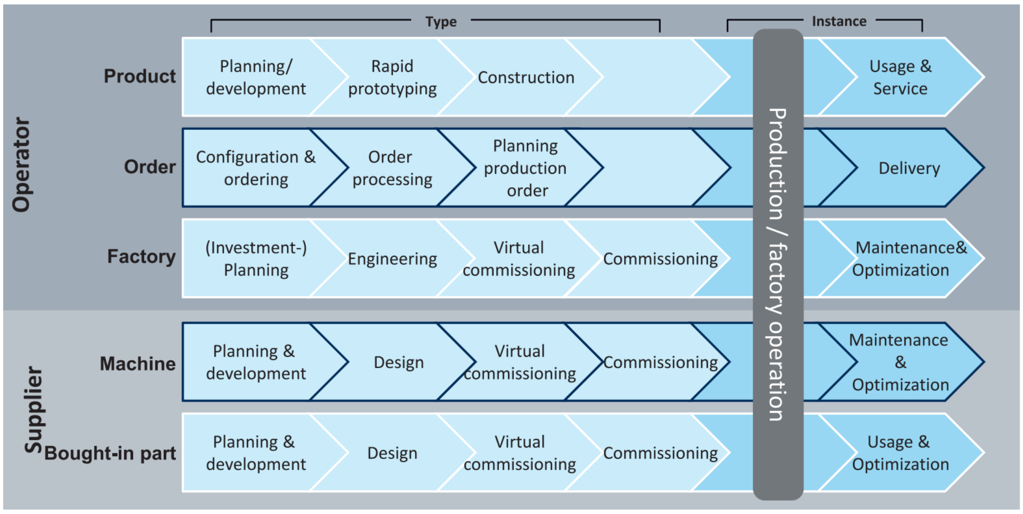


Fig. 6.5: *Relevant life cycles for I4.0 components; Source: M. Hankel, Bosch Rexroth. Based on Plattform Industrie 4.0 WG3. Based on Prof. Bauernhansl, Fraunhofer IPA Copyright "Umsetzungsstrategie Industrie 4.0 – Ergebnisbericht, Berlin, April 2015" [Adolphs & Epple 2015]*

The life cycle axis in RAMI 4.0 distinguishes between the "Type" and "Instance", and the meaning is further explained in Figure 6.5. The intended outcome is to be classified under the "Type" which can be used in the life cycle of a machine, for example. Adding to what is illustrated earlier in Figure 6.2, the focus is to be on the early design phases up to the commissioning.
Considering the third axis, the electric drive can be classified under the "Field Device".

Chapter summary

As it is aimed to link energy flexibility with the design of manufacturing systems (Research objective 1), and to use component-based design approach in the manufacturing system's engineering (Research objective 3), this chapter discussed the means of achieving this in terms of tools and methodologies.

It is proposed by many researchers to extend the architecture of manufacturing systems to be in harmony with energy demands. Therefore, based on the design tools, methods and methodologies of CPS, it is shown that energy consumption can be taken into account as a design parameter. More specifically, the focus is put on the component level, as energy flexibility literature, to date, has not provided sufficient insight into it. Energy flexibility can have granularity, and design and control levels similar to the manufacturing system. Therefore, it can potentially be harmonised with the manufacturing system life cycle design.

The possible support of sustainable manufacturing through virtual engineering has been shown and the foundation of building energy-flexible components is explained, taking into account the coverage of the manufacturing system life cycle. It has been shown in Chapter 6 that data-based methods are recommended for energy consumption modelling. Further step is taken by proposing the inclusion of data-based models in the developed energy-flexible components, by following a map that is inspired by RAMI 4.0. This concept is novel theoretically and will be validated empirically and will be validated in the next chapter.

Chapter 7

An Empirical Evaluation of the Proposed Approach

"Contradiction is not a sign of falsity,
nor the lack of contradiction a sign of truth"
— **Blaise Pascal**

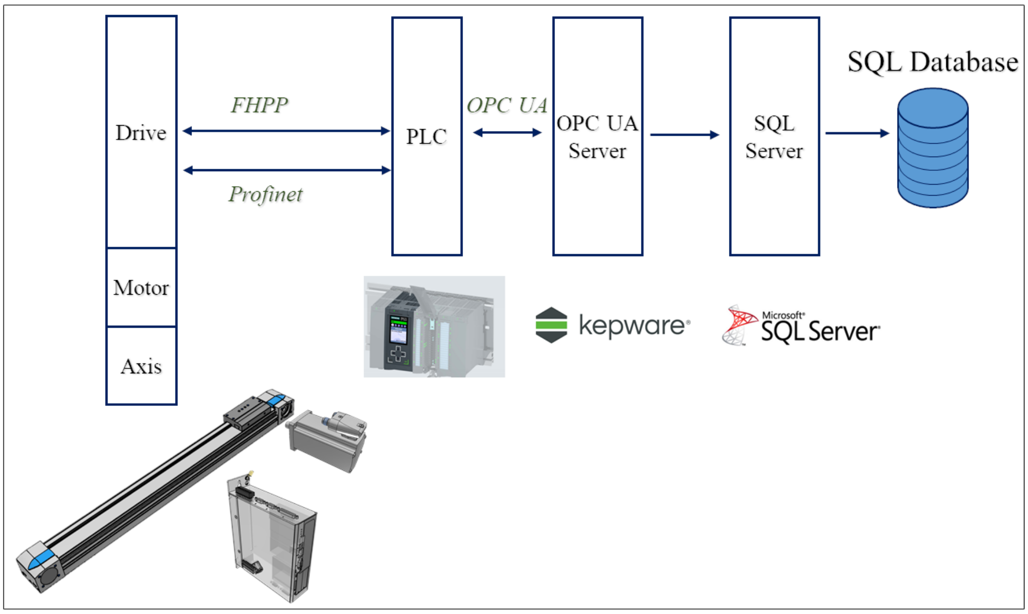
THis chapter demonstrates an empirical validation of the proposed methodology. A bottom-up approach is followed by studying an electrical drive as a manufacturing system component. Then, the procedure proposed in Figure 6.4 is implemented in three phases. The first phase concerns with energy consumption modelling and prediction (the work is focused on the physical aspect), whereas the second phase concerns with the life cycle design by building the virtual model (the cyber aspect). The third phase looks into connecting external services.

7.1 Phase I: Experimental set-up

7.1.1 The elements of the experiment

Figure 7.1 shows both a schematic and an actual image of the experiment's elements. In the following paragraphs, a brief explanation of each of them is provided.

–**Festo electric drive**: a combination of an electric drive (motor controller), a motor



(a) *A schematic of the experiment*

(b) *A view of the experiment's physical devices*

Fig. 7.1: *The physical components of the experiment*

and an axis from Festo are connected together as a component. "Festo Handling and Positioning Profile (FHPP)" is a data profile developed by Festo for positioning applications. With FHPP, motor controllers can be controlled using a Fieldbus interface via standardised control and status bytes. The drive is integrated with a Festo motion controller via a built-in CAN interface. The drive controls a brushless, permanently excited synchronous servo motor that is compatible with it. A toothed belt axis is actuated by the motor to perform the linear motion of the actuator within a distance range (0-450 mm).

–**Siemens S7-1500 PLC**: The SIMATIC S7-1500 is the modular control system for numerous automation applications in discrete automation [Siemens 2016]. This PLC works as a hub that controls the on/off states of the component, communicates some motion parameters/controls, and functions as a data collection point. The PLC communicates with the drive via Profinet and uses FHPP protocols.

–**KEPServerEX**: This is a leading industry connectivity platform that provides a single source of automation data to a great variety of applications [Kepware n.d.].

Using KEPServerEX, data is provided for client applications, IoT, and Big Data analytics software, via OPC. RAMI 4.0 lists the IEC 62541 standard OPC Unified Architecture (OPC UA) as a recommended solution for implementing the communication layer [ZWEI 2015].

–**SQL Server**: It is a relational database management system, developed and marketed by Microsoft. The server is built in support of the standard SQL programming language. It contains a database engine and SQL Operating System (SQLOS). The database engine consists of a relational engine that processes queries and a storage engine that manages database files [SQL Server Tutorial n.d.].

7.1.2 Experiment's set-up

To have the experiment's elements ready to perform the motion tasks, and the data ready to be collected and then processed, a number of the configurations have to be implemented. This includes establishing the communication channels and setting up the intended storage databases.

7.1.2.1 Drives and axis configuration

To enable the interaction between the drive, the motor and the axis, these elements have to be configured using the Festo Configuration Tool (FCT) as a 'project' to be downloaded later to the drive memory. Figure 7.2 shows the assignment of these elements to the project file in addition to defining the interface with the PLC (Profinet in this case) and the installed safety module. In addition, the homing method, the positioning method, control method parameters (e.g. current and velocity gain) and the Fieldbus configuration are set using this tool.

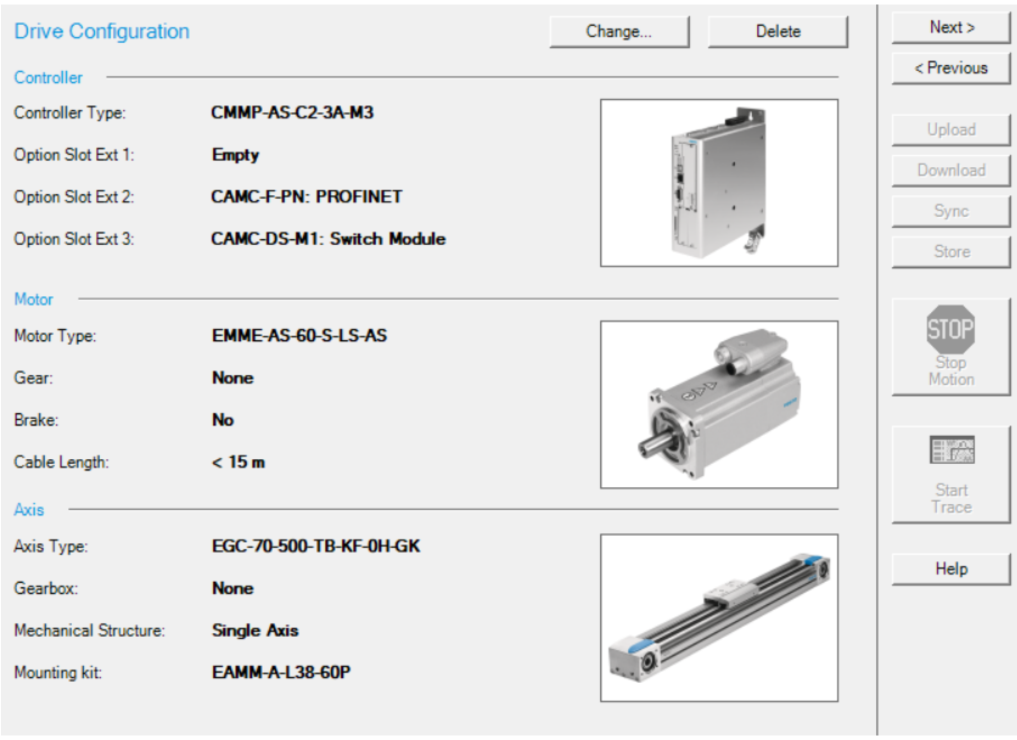


***Fig. 7.2:** The configuration of drive components in FCT*

Most importantly, the messages (data) to be exchanged with the PLC are also specified using this tool by using the data profile FHPP mentioned earlier. The implementation of this will be further detailed under the PLC configuration. Once the 'project' is downloaded and saved to the drive's memory, FCT allows testing of the motion and some of the messages exchanged with the PLC. Please note that the implemented configurations, whether for the PLC or the drive, are briefly described here.

7.1.2.2 PLC hardware and software configuration

PLC's hardware configuration involves creating a PLC project on Totally Integrated Automation portal (TIA portal) software (for Siemens PLCs) which is downloaded later to the PLC's memory. After assigning the devices' IPs, the drive's GSD file is added to the project. The GSD file contains the configuration information of the device in addition to its parameters and modules when using the Profinet protocol. By the end of hardware configuration, the PLC can recognise the drive and can communicate with it but a further configuration is needed to achieve data interoperability. Figure 7.3 shows the successful connection by the end of the hardware configuration.

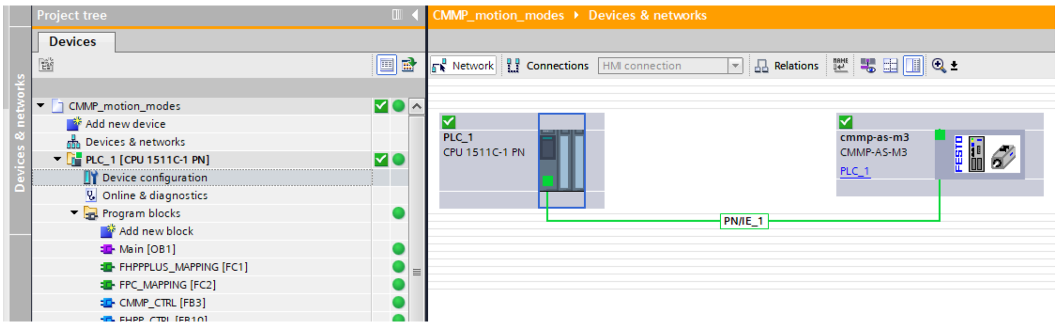


Fig. 7.3: Establishing successful connection after hardware configuration

For the software configuration, the drive's motion library consistent with the PLC has to be added, and the data profile FHPP has to be defined. Furthermore, the parametrisation capability called (FHPP+) should be added as well so that the internal parameters of the drive (e.g. current, velocity etc.) can be accessed.

The function blocks necessary for motion are added to the PLC programme, then the hardware identifiers are modified. These function blocks accomplish the tasks of Reading (RD), Controlling (CTRL) and Writing (WR) to the drive. Figure 7.4 shows example function blocks that accomplish the control and write functions. Along with

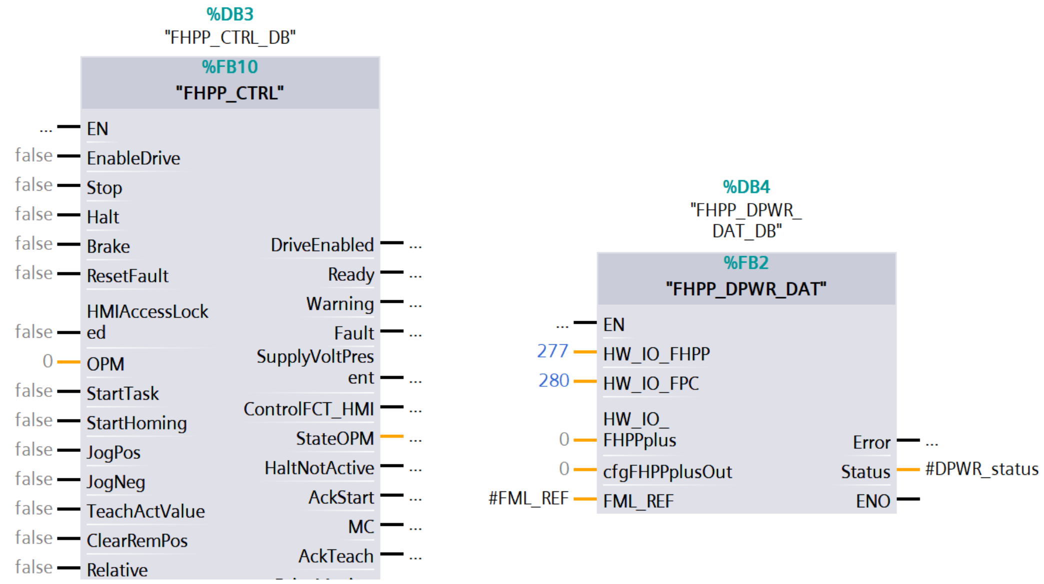
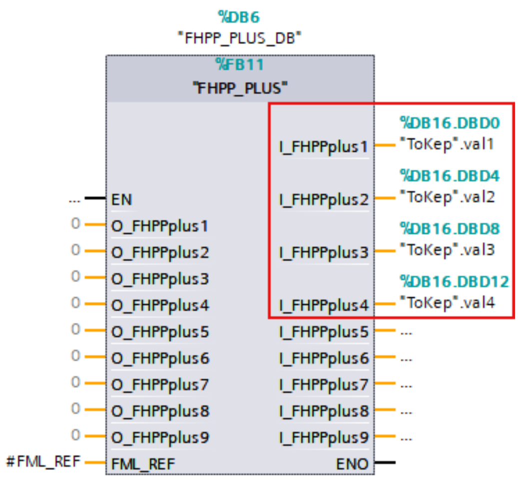
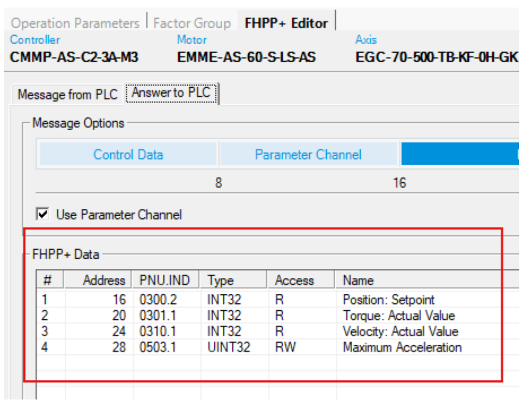


Fig. 7.4: *Exemplary function blocks*

creating these function blocks, the necessary data types have to be added according to the manual instructions and depending on the device type. If the setting of FHPP is successful, the basic tasks of the drive such as homing, jogging and moving to a specific point can be achieved. For setting up FHPP+, hence, reading the internal parameters, the activation block should be added on the drive's programme, and loaded on the PLC programme accordingly as shown in Figure 7.5.



(a) *FHPP+ function block*



(b) *FHPP+ drive editor*

Fig. 7.5: *Sending FHPP+ data from the drive to the PLC*

FHPP+ offers the possibility of reading a variety of parameters. However, a limited number (depending on the parameters memory size) can be sent to the PLC. Figure 7.5b shows the specified parameters on the drive to be sent to the PLC, whereas Figure 7.5a shows the function block that receives them in the PLC programme.

7.1.3 Data collection and storage method

It is well known in industrial practice that PLCs are often limited in terms of the available storage memory. Furthermore, storing data in a PLC's data block then extracting them into Microsoft Excel files or Access, for example, is not straightforward. Here, a great capability is offered by KEPServerEX OPC UA which acts as an IoT protocol. By using KEPServerEX, data can be transferred in real-time and stored in various formats. To take advantage of this opportunity, the tags corresponding to FHPP+ parameters are identified in KEPServerEX. The scanning rate is chosen to be 100 ms, as 100 ms or less was found to be the best rate with regards to data quality (Figure 7.6). The quality of data is assessed based on the sufficient number of points to represent the motion, and the corresponding electrical power consumption.

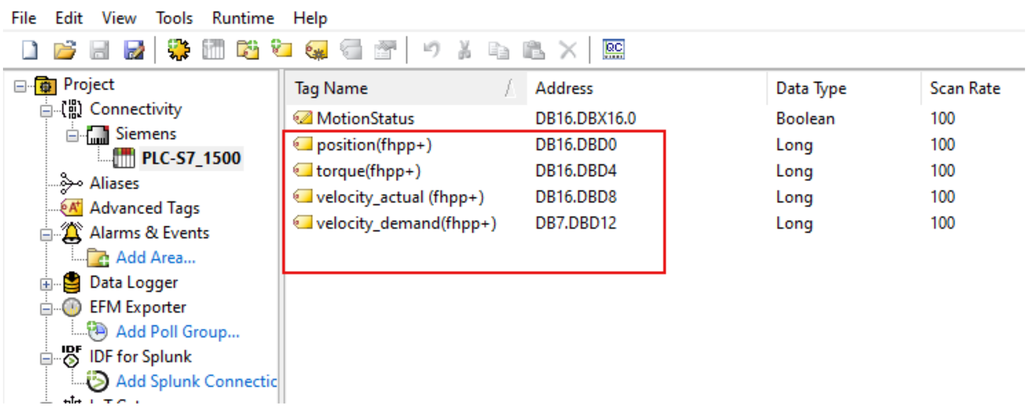


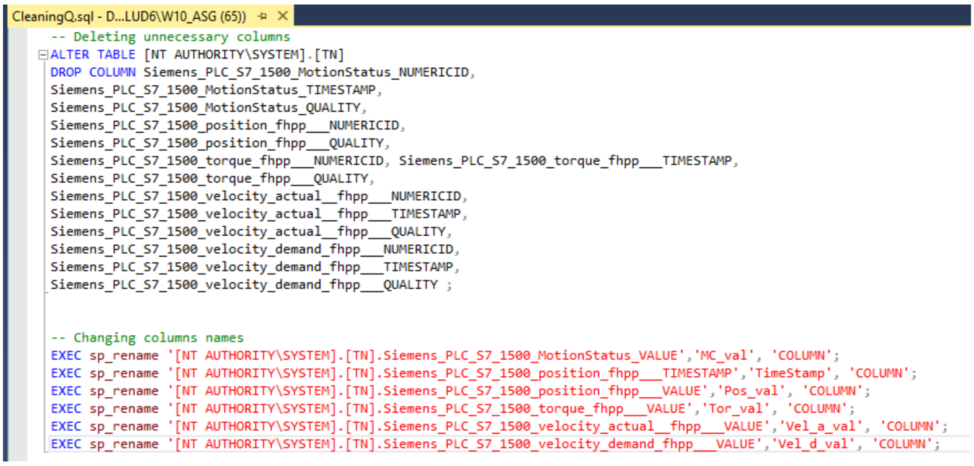
Fig. 7.6: *Importing FHPP+ parameters to KEPServerEX*

KEPServerEX contains a Data Logger that can be customised to store certain features of the assigned tags, such as their quality and sampling rate, not only their values. In addition, some tags can be specified as 'triggers' for the logging process.

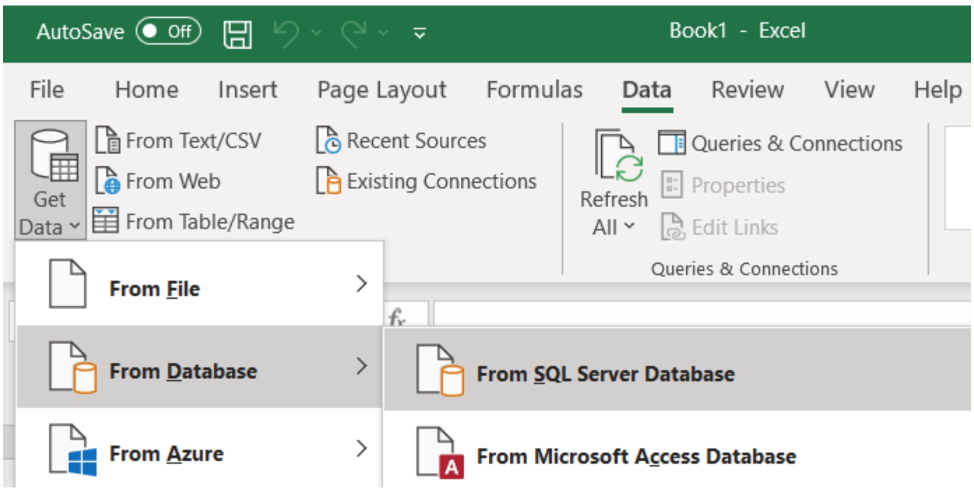
To store the data imported to KEPServerEX, a connection between an SQL server and KEPServer has to be established. It should be noted that Data Logger can store the captured data in formats such as Microsoft Excel, however, the accuracy of time samples will be lost as the minimum time stamp in Excel is in seconds not milliseconds. Therefore, SQL server has to be utilised.

7.1.4 Data preparation

The databases, used to save data obtained via KEPServerEX Data Logger, contain multiple features for each tag such as the Numeric ID, timestamp, quality, etc.



(a) SQL query written to as part of data preparation



(b) Importing data from SQL database to Excel

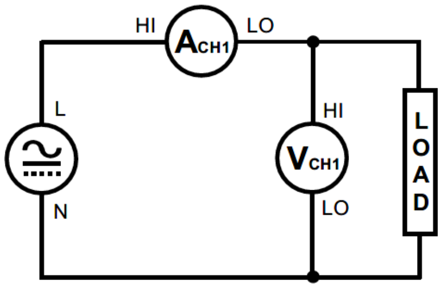
Fig. 7.7: *Data preparation using SQL and Excel*

In order to remove unnecessary logged data (to reduce the data volume), suitable SQL queries are written in the standard SQL programming language. An example of a 'cleaning' query is shown in Figure 7.7a. After removing the unnecessary data columns, the SQL database content is imported via excel (Figure 7.7b) where it can be easily converted into other formats (e.g. CSV) or read by other programming languages (e.g., Matlab, Python).

7.1.5 Energy consumption measurement

As shown in Figure 7.1b, a power analyser device PPA5500 is used to measure power consumption at the drive input (Figure 7.8a).

***(a)** Power analyser PPA 5500*



***(b)** Wiring plan when measuring single phase power*

***Fig. 7.8:** Power analyser and the used wiring plan*

The drive operates at a nominal voltage of 230 V and a nominal current of 2-3 A (single phase). Therefore, as per the power analyser documentation, the wiring plan shown in Figure 7.8b is implemented so that power consumption at the drive input can be measured. PPA5500 was set to measure power data with a timestamp of 100 ms. The outputted logs can be in the CSV format or standard Excel files format.

Measurement controls, including the measured quantities and sampling rate, were set via a graphical user interface with the possibility of saving various measurement configurations. However, the connection used to transfer data is an Ethernet one which limits the sampling rate. There was a possibility to use an IoT energy meter (from Schneider Electric) but the minimum given sample rate of this device is 1 second which is not enough for the application in hand.

7.2 Phase I: data analysis

7.2.1 Drive trajectory behaviour

Figure 7.9 shows a sample of the trajectory implemented in the studied Festo drive.

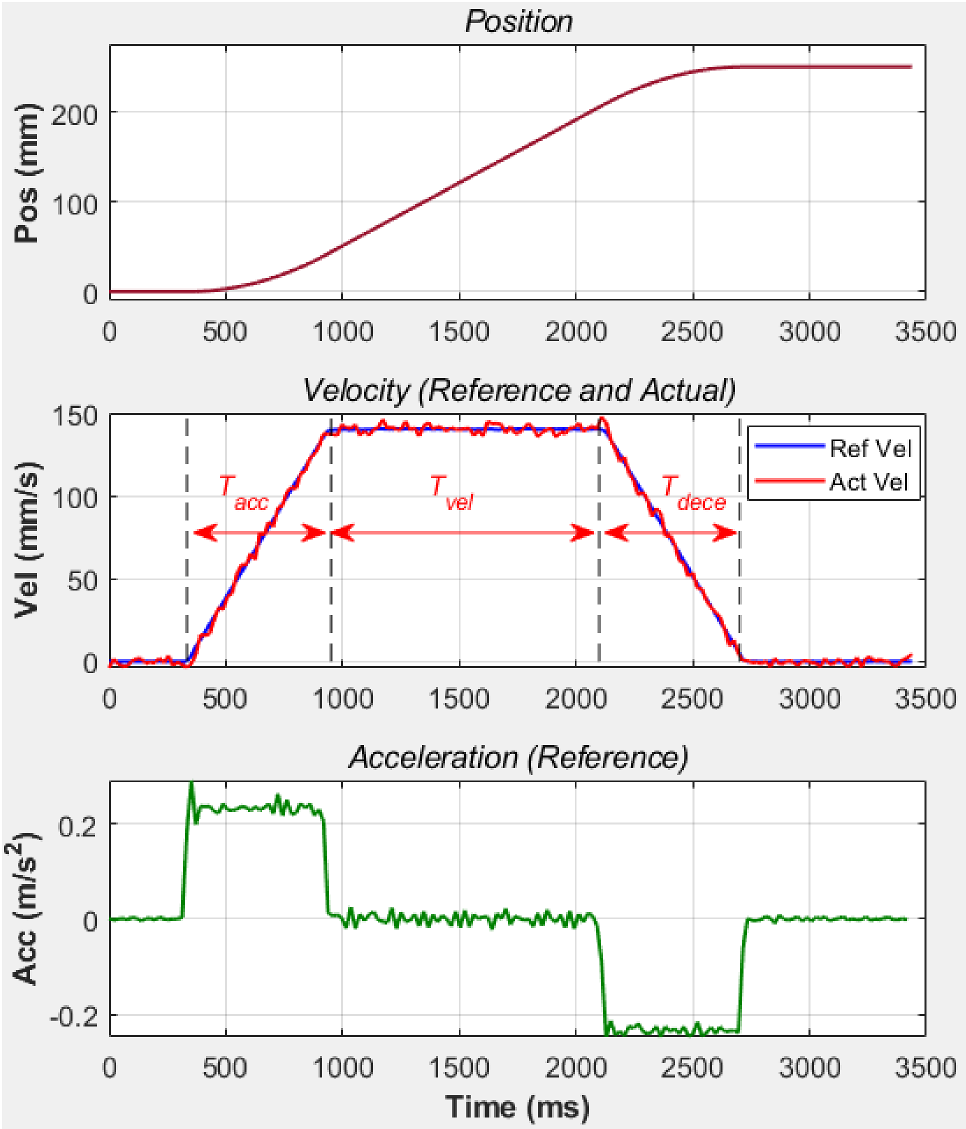


Fig. 7.9: *An example of the trajectory*

The drive position is of a high accuracy that is 0.1 mm (in the context of the intended pick and place application). Looking at the reference values for both velocity and acceleration, it can be noticed that the reference trajectory is an s-curve.

The configuration tool offers the possibility of smoothing the profile, however, this would increase the cycle time. Smoothing takes place by increasing the acceleration rise time. Smoothing takes place by increasing the acceleration rise time. As explained earlier in Chapter 5, increasing the acceleration's rise time limits the jerk, which is desirable to manage machine vibration reduction/elimination. The trajectory depicted in Figure 7.9 is with 0% smoothness, i.e., the shortest cycle time. The manufacturer of the drive does not offer a formula for calculating the motion cycle time, but only the formula of the acceleration's rise time (T_{acc}) and fall time (T_{dece}) as a function of the maximum velocity (V_m) and the maximum acceleration (A_m), which is:

$$T_{acc} = T_{dece} = \frac{V_{max}}{A_{max}}$$

To calculate cycle time, it is aimed to find T_{ct} where (Figure 7.9):

$$T_{ct} = T_{acc} + T_{vel} + T_{dece} \tag{7–1}$$

The motion equation that governs T_{acc} period is:

$$a(t) = A_{max}$$

$$v(t) = A_{max}t + v_0$$

$$s(t) = \frac{1}{2}A_{max}t^2 + v_0t + s_0$$

Assuming that the distances crossed in the periods T_{acc}, T_{vel}, T_{dece} are s_{acc}, s_{vel}, s_{dece} respectively, the initial conditions are $s_0 = 0$, $v_0 = 0$ and the targeted position is S_f:

$$s_{acc} = \frac{1}{2}A_{max}T_{acc}^2$$

Then, if $T_{acc} = T_{dece}$, it yields:

$$s_{acc} = s_{dece}$$

$$s_{vel} = S_f - (s_{acc} + s_{dece})$$

The motion equation that governs T_{vel} period is:

$$v(t) = V_{max}$$

$$s(t) = V_{max}t + s_0$$

Thus:

$$s_{vel} = V_{max}T_{vel}$$

$$T_{vel} = \frac{s_{vel}}{V_{max}}$$

Substituting the terms T_{vel},T_{acc}, T_{dece} in equation 7–1 gives:

$$T_{ct} = \frac{V_{max}^2 + A_{max}S_f}{A_{max}V_{max}} \tag{7–2}$$

Using equation 7–2, it is possible to calculate the cycle time based on the input set points when there is no required smoothness (highest productivity), and for a symmetrical motion profile which is most commonly used.

7.2.2 Drive energy consumption

The drive is doing mechanical work that is the motion (whether loaded or unloaded). Attempting to calculate the mechanical work involves including energy losses due to friction between the moving part and its rail, in addition to other losses due to motion transmission parts.

The drive's principle of work relies on varying the electrical current value while maintaining the voltage at a certain value. Thus, the resultant torque is controlled in order to obtain the targeted set points of velocity or acceleration by controlling the frequency of the motor shaft's, i.e., its rotational velocity which in turn implies the change of the associated linear velocity. The change of velocity values, compared to the current values, is shown in Figure 7.10, and illustrates the similarity of their behaviour. When velocity rises, more current is needed to achieve the required acceleration, whereas when velocity falls, the fall of current is not necessarily as sharp as its rise. The nominal operating voltage is 230V ± 10% and remained within this range in the experiments.

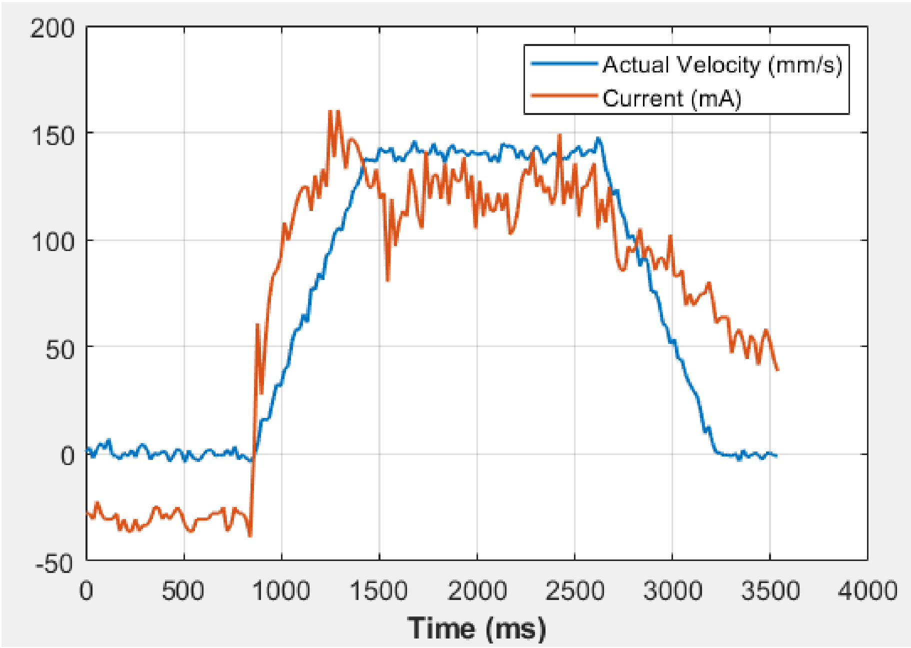


Fig. 7.10: *The change of velocity and current with time*

Once the drive's input current is received, it has to pass through a rectifier, DC bus and an inverter [Evans 2020]. The rectifier converts current from AC to DC. Next, the DC bus capacitor smooths the voltage by filtering ripples. Then, the inverter controls the direction and frequency of the output. These operations all involve some loss of energy.

From an applied sciences' perspective, it would be possible to study the mechanical and electrical losses by modelling both the mechanical and electrical systems. However, for manufacturing system design, performing this for every component is effortful. The argument to put forward here is that tracing the velocity and acceleration of the drive should give a good indication of the consumed energy/ power. Therefore, a machine learning approach that depends on the collected data is proposed to identify the resultant energy consumption.

7.3 Phase I: prediction of drive's energy consumption

7.3.1 Implementation and results of MLR

For supervised learning, Mattmann [2020] suggests using the rule 70-30 where 70% of the data are used to train the model and 30% are used to test it. However, in this work, a 50-50 principle is considered for further credibility of the implementation. The number of samples used for the model is 500. The vector X for a sample n contains the input parameters, whereas the vector Y is the value of consumed energy.

$$X_n = [S_{f(n)} \quad V_{max(n)} \quad A_{max(n)} \quad T_{ct(n)}] \tag{7–3}$$

$$y_n = E_n \tag{7–4}$$

The value of energy is calculated using the numerical integration (trapezoidal rule function) of the detected electrical power values over sampling time data points (Figure 7.11):

$$E_n = \int_{t_0}^{t_f} (p_n) dt$$

Figure 7.11 shows the meaning of each of the vectors X, Y components for one sample. To compare the predicted energy values to the experimental ones, the difference as a percentage of the original values is calculated using the formula:

$$\epsilon = \frac{|E_{pr} - E_{ex}|}{E_{ex}} * 100 \tag{7–5}$$

It is possible to implement the MLR algorithm by programming it in Matlab or Python or using the ready Python standard library 'scikit-learn' with all the aforementioned methods giving the same result. After utilising 300 samples (half of the total collected data) for training the model, the predicted results were evaluated against the experimental results, then the error was calculated using the formula 7–5. The calculation is performed using a computer whose Central Processing Unit (CPU) is Intel®Core^{TM} i5-6500 CPU @ 3.20 GHz and with an installed Random Access Memory (RAM) of 8.00 GB. Elapsed calculation time in Matlab is 0.000984 seconds.

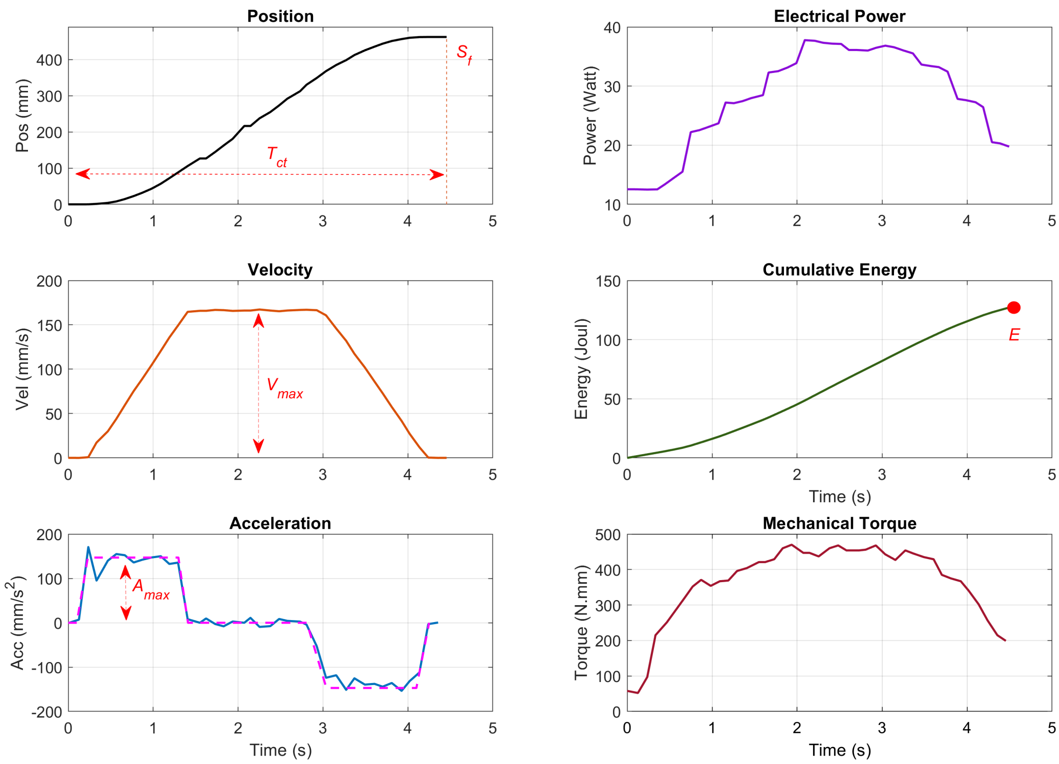


Fig. 7.11: *A representation of the data deployed in MLR model (for one sample)*

Figure 7.12 shows the results in terms of the predicted values compared to the actual experimental ones. In addition, some of the numerical values are shown in Table 7.1.

S (mm)	V_{max} (mm/s)	A_{max} (mm/s^2)	T_{ct} (s)	y_{ex} $(Joul)$	y_{pr} $(Joul)$	ϵ (%)
121.3	112.6	118.58	2.27	49.6906	49.6674	0.047
261.5	103.51	87.17	3.89	102.4899	100.9625	1.51
79.8	120.81	197.39	1.883	37.9863	36.6666	3.59
302.1	155.77	82.83	4.083	105.9425	104.2428	1.63
322	53.66	48.29	7.604	181.9756	186.7021	2.53
10	19.81	47.014	1.09	17.2036	21.0222	18.16
233	103.96	79.48	3.97	93.5665	98.4637	4.97
110.2	19.4	14.10	7.393	144.0446	157.0651	8.29

Table 7.1: *Exemplary results of MLR outcome*

The pie chart in Figure 7.12 summarises the outcome of MLR where around 79%

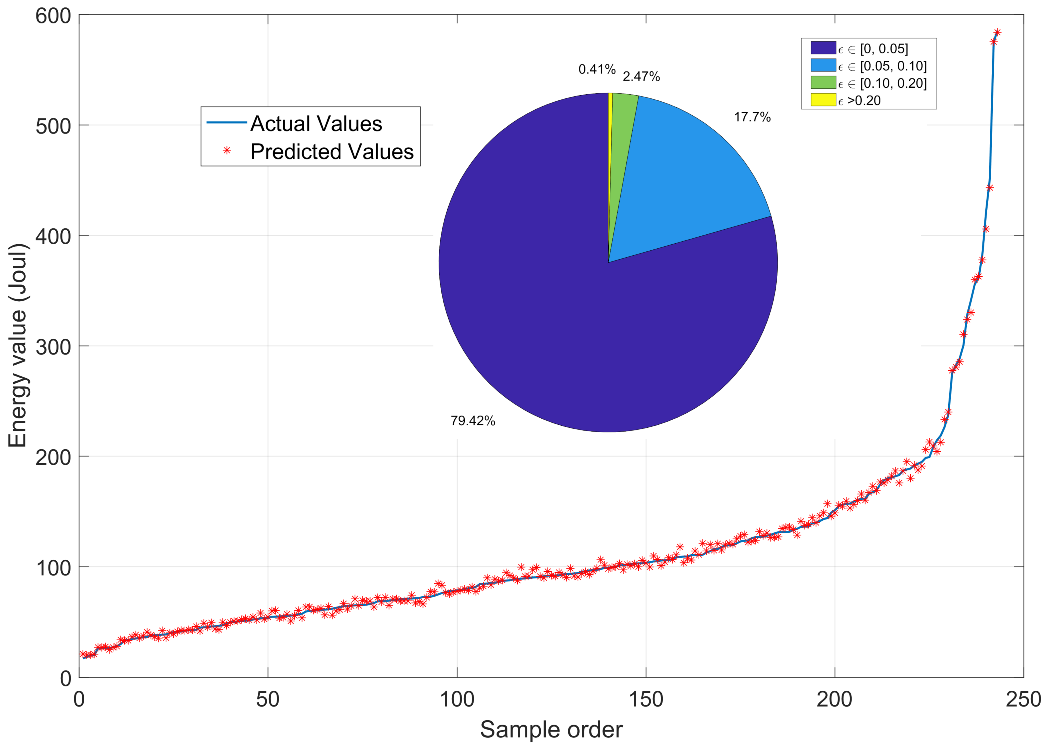


Fig. 7.12: *Predicted energy consumption values using MLR vs. the actual experimental values*

of the predictions have an error that is less than 5%, whereas only less than 1% have an error over 20%.

7.3.2 Implementation and results of Deep Learning

The same data used in MLR are used to train and evaluate the created deep learning model. The model was built in Python and a variety of libraries were utilised:

- Building deep learning model: Tensorflow and Keras.
- Manipulating data and splitting them into testing and training groups: Sklearn, Numpy, Pandas.
- Data visualisation Matplotlib.

The next step is to import data (in the form of a CSV file) and extract it to suit the accepted format of the model's inputs. Then, the model is built of one input layer, two hidden layers (each of the first has 1024 neurons, the second has 256 neurons) and the output layer. Further specifications of the model have to be configured and are shown in Table 7.2.

Feature/Attribute	**Specification**
Optimiser	Adam
Learning rate	0.001
β_1	0.9
β_2	0.99
Activation function	Relu
Loss function	Mean Absolute Error
Epochs	200

Table 7.2: *A summary of the specifications used in deep learning model*

The selection of these specifications is based on multiple trials to improve the performance of the model in terms of solution quality (reduced error) and time efficiency (less calculation time). The calculation is performed using a computer whose Central Processing Unit (CPU) is Intel®Core$^{\text{TM}}$ i5-6500 CPU @ 3.20 GHz and with an installed Random Access Memory (RAM) of 8.00 GB. Elapsed calculation time in Python is 5.39 seconds.

In the implementation, data were divided into testing and training data (50% each, similar to the implementation of MLR. Figure 7.13 shows the results of the data fitting. It can be noticed that both MLR and DL could fit data properly, thus the created models can predict the drive's energy consumption with a good level of credibility.

In relation to this, further comparison of the outcome of both Deep Learning and MLR methods is performed in Table 7.3. It can be noticed that the accuracy is improved by using Deep Learning where the error ϵ decreases as shown from pie charts and the calculated values in Table 7.3. In general, good predictions are obtained, however, the computation cost, time and implementation effort are more when using Deep Learning.

In the following sections, these results will be further invested in building an optimisation algorithm, and then a virtual engineering model for the purpose of improving energy flexibility.

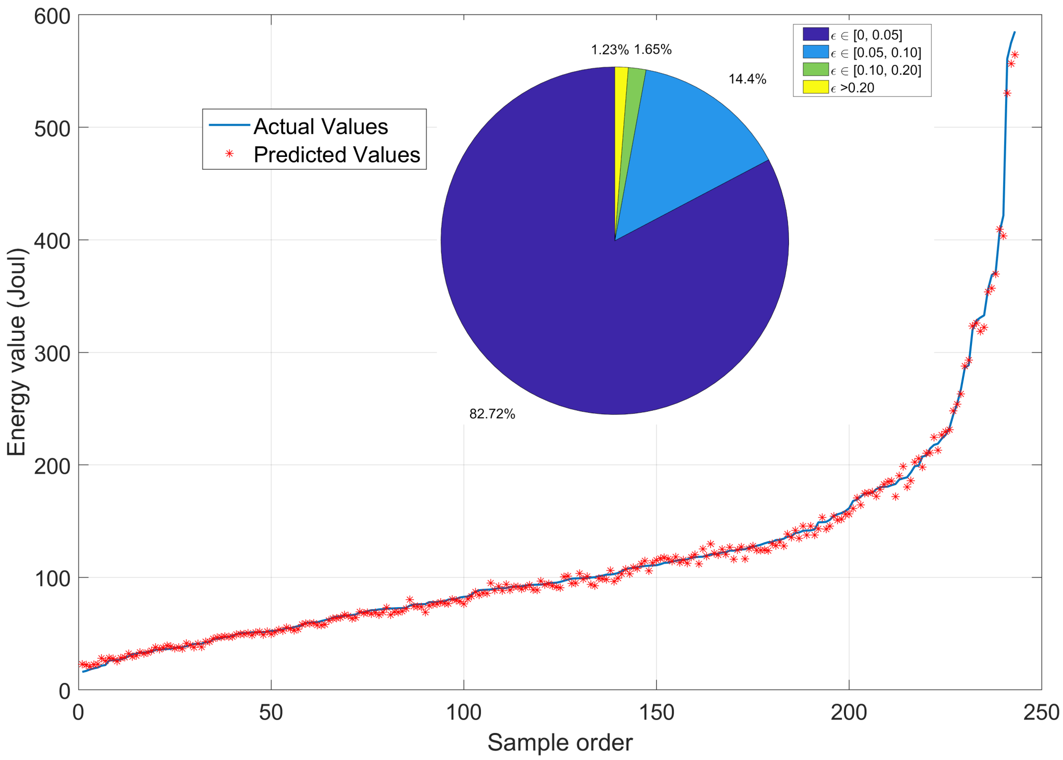


Fig. 7.13: *Predicted energy consumption values using Deep Learning vs. the actual experimental values*

ϵ	**MLR method**	**Deep Learning method**
$\epsilon \in [0, 0.05]$	79.42%	82.72%
$\epsilon \in [0.05, 0.10]$	17.7%	14.4%
$\epsilon \in [0.010, 0.20]$	2.47%	1.65%
$\epsilon > 0.20$	0.41%	1.23%

Table 7.3: *A comparison between the outcomes of Deep Learning and MLR*

7.4 Phase II: Virtual engineering and energy-flexible component

7.4.1 Overview and necessary tools

To build the digital twin of the studied component, it is necessary to [Tao et al. 2019]: build a virtual representation of physical counterpart using CAD or 3D modelling, simulate and test the physical system in a virtual environment, and establish real-time bi-directional secure connections between the physical and the cyber system. To achieve this, in addition to the elements of the experiment elements mentioned earlier in 7.1.1, further tools are necessary for building the digital twin and potential tools of decision making which are Visual Components™ and Node-RED.

Node-RED is a programming tool originally developed by IBM based on Node-js which is an open-source JavaScript runtime environment. Node-RED provides a browser-based editor that allows the creation of flows of the programming instructions in addition to certain function blocks which accept Java codes, whereas some accept Python as well but are less developed. The flows created in Node-RED can be stored using JSON (JavaScript Object Notation), imported easily and exported for sharing with other users. Node-RED is regarded as an invaluable tool for developing IoT solutions as it enables solution developers to control and visualise the workflows of data [Hernández 2018]. Another advantage of using Node-RED is the possibility of creating Graphical User Interfaces (GUIs) with dashboard elements, which enables the visualisation of parameters' behaviour.

Visual Components, as referred to on the products homepage, is 3D manufacturing simulation software that aids machine builders, manufacturers and system integrators in developing cost-effective, simple and quick solutions. Visual Components helps to build the virtual model of the layout, work cell or the components involved in manufacturing (e.g., robots) [Mikhail et al. 2020]. Moreover, it supports recording controls and the running of Python scripts to perform certain user commands. This tool's main benefit, in relation to this work, is its ability to create the virtual model of the component, in addition to the necessary connection channels with the PLC, external server, and external software services. Furthermore, Visual Components can help to support the 'reuse' of components in future designs, making the design process more sustainable [Assad et al. 2021] as shown in the rest of this chapter.

7.4.2 Modelling in Visual Components

The 3D representations of both the axis and its driving motor were provided from the manufacturer's website (Festo). Then, they were added to a blank virtual model in the Visual Components environment as shown in Figure 7.14. It should be noted that the geometry of the motor is added for visualisation purposes only. The targeted simulation changes are related to the axis's motion.

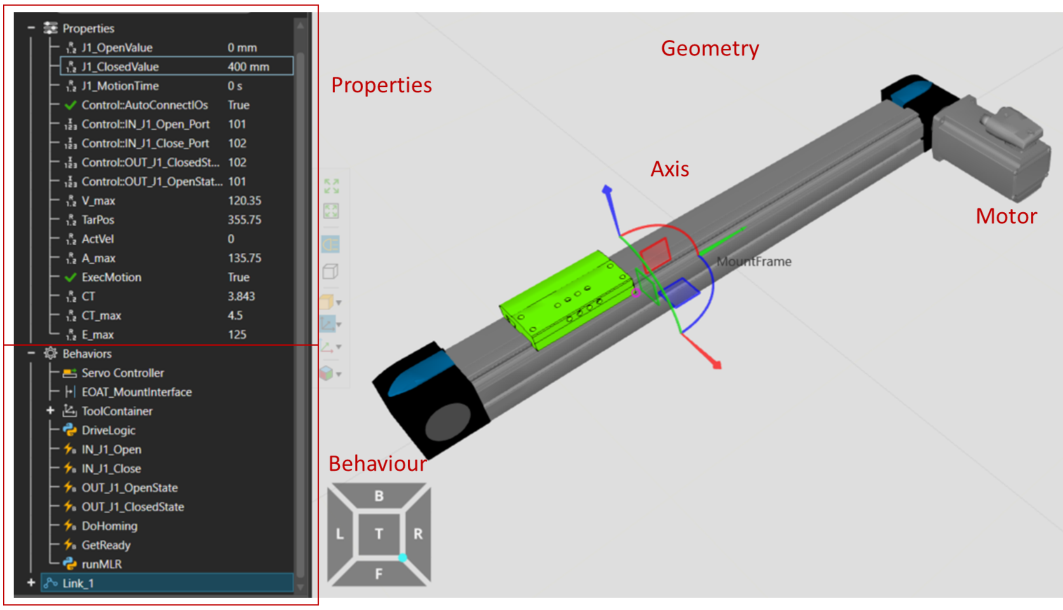


Fig. 7.14: Creating the virtual model of the studied component

The next step is modelling both the kinematics and the controls. Visual Components defines each component with a group of behaviours and properties (Figure 7.14). Control signals are stored under the behaviours in addition to the necessary codes (Python scripts) added by the user. Under the component properties are numerical and logical values that may affect the programmed behaviours, and can be mapped to the values related to the physical model. For example, one of the studied axis properties is the maximum distance.

After setting the geometry, the physical behaviour of the component has to be modelled. Therefore, a translation joint is defined as j_1 (Figure 7.14). Next, the properties of the joint such as the minimum and maximum limits, and the motion's positive direction are entered. Once the translational joint is created, corresponding control ports are automatically generated by the software.

To define the "control logic", the created translational joint has to be connected to a "Servo Controller" element. Once this controller is added, a "DriveLogic" script which contains the basic code instructions (in the form of Python functions) is created. It can be noticed that behaviour signals are linked to the component properties using the code in "DriveLogic".

The final step in control configuration is to create signals corresponding to the ones in PLC programming e.g. "GetReady", "DoHoming" where the former enables the servo motor, and the latter instructs the motion controller to drive the joint to its zero point.

7.4.3 Energy consumption prediction in the virtual model

To obtain an energy flexible component, the ability to predict energy consumption is to be added when the component is being designed as an element of the manufacturing system. Then, it has to be callable by the virtual model (which evolves into a digital twin). Furthermore, the obtained component should be adaptive, i.e., capable of reconfiguring the parameters that influence energy consumption. For the previous argument to become a reality, a collaboration between simulation capabilities, information processing means, and communication channels has to be established.

Two methods of predicting energy consumption were introduced earlier, namely, MLR and Deep Learning. Taking advantage of the mathematical simplicity of MLR, and Visual Components' behaviour scripting possibility, coding MLR in a Visual Components Python script is implemented.

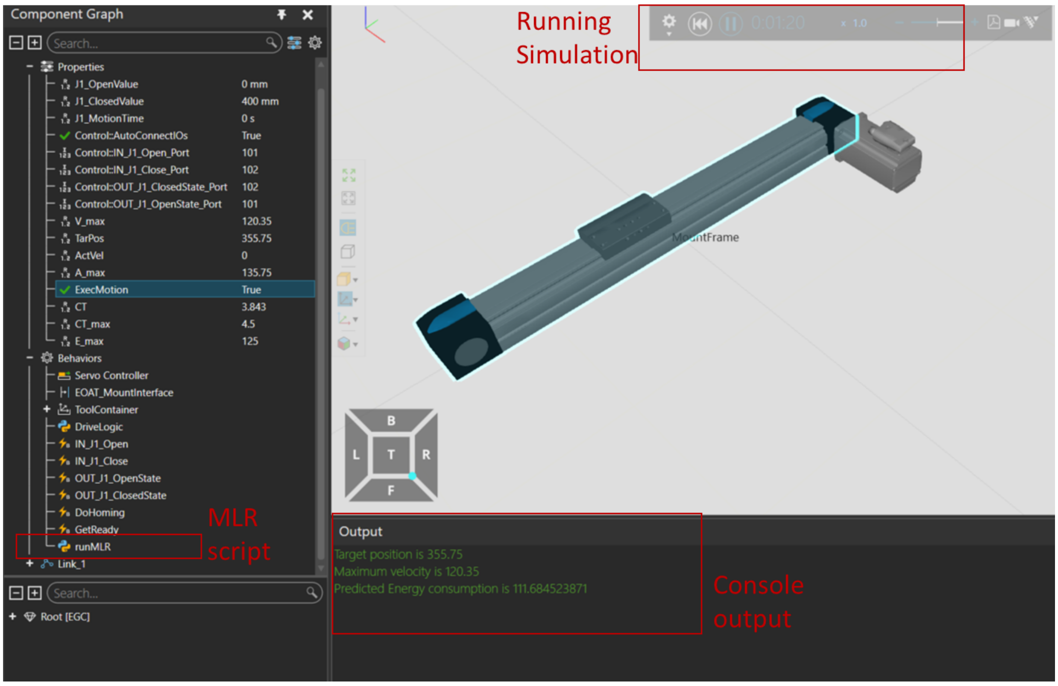


Fig. 7.15: *Prediction of component's energy consumption in Visual Components environment*

Figure 7.15 shows that the MLR prediction method was added to the component's behaviour, then once the simulation is run, the console output of Visual Components displays the calculated prediction of energy consumption. In this script, equations 7–3 and 5–4 are executed where the vector X is obtained from designer inputs and β is already stored based on the findings of 7.3.1. Hence, predicted energy consumption is the scalar product of those two vectors.

For Deep Learning, it was not applicable to integrate it into the Visual Components environment as it requires external Python libraries that cannot be added to the software (e.g. TensorFlow and Numpy), and also because of the complexity of the DL prediction model compared to MLR. The DL model is represented by a certain type of file (.h5) which cannot be read by Visual Components. Nevertheless, a DL method was developed using Node-RED, and will be explained later in 7.5.1.

7.4.4 Establishing connectivity to the physical model

For the developed virtual model to become a "digital twin", successful communication with the physical model has to be established with the ability to exchange data and to report changes. A map of the communications established between the virtual model, physical model (PLC basically), KepServerEX and Node-RED is shown in Figure 7.16.

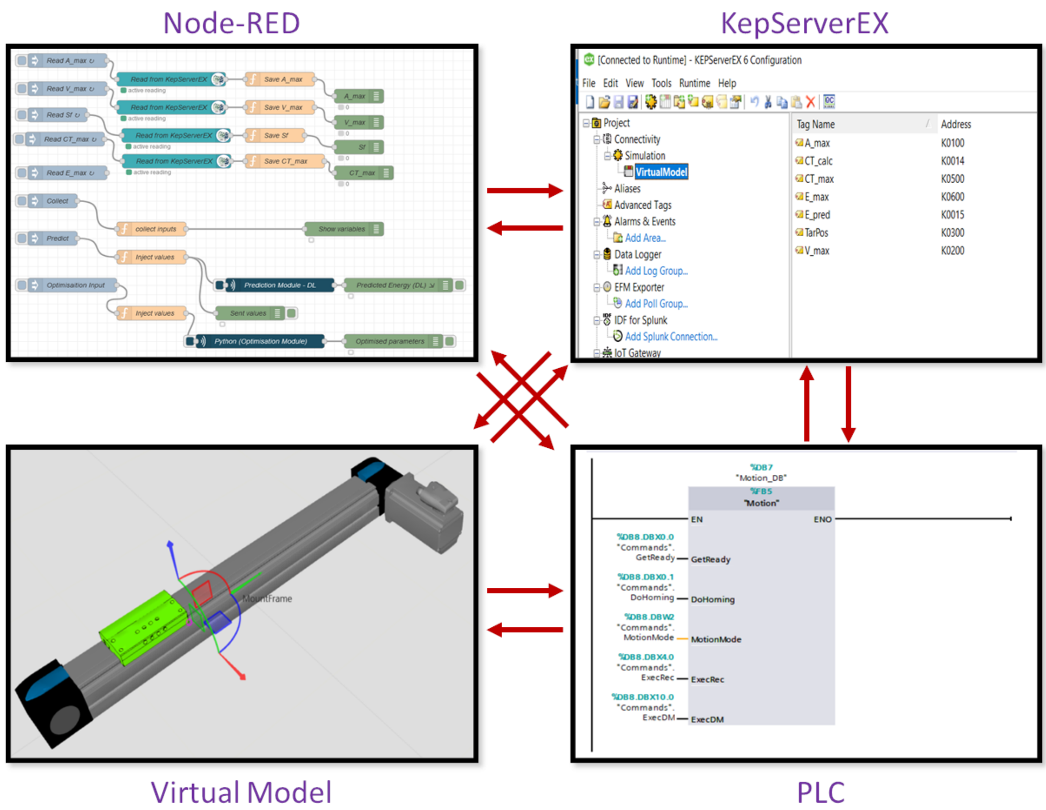


Fig. 7.16: *Connectivity map of the entities involved in this work*

In this architecture, Node-RED is used as a platform to run and communicate with external services, e.g., Python scripts and the GUI interface. Meanwhile, KepServerEX is used as a communication agent that guarantees to connect the physical and cyber component's parts to Node-RED. It should be noted that Node-RED could not be connected to Virtual Components, seemingly for security reasons. To overcome this problem, the KepServerEX is utilised as a data exchange medium.

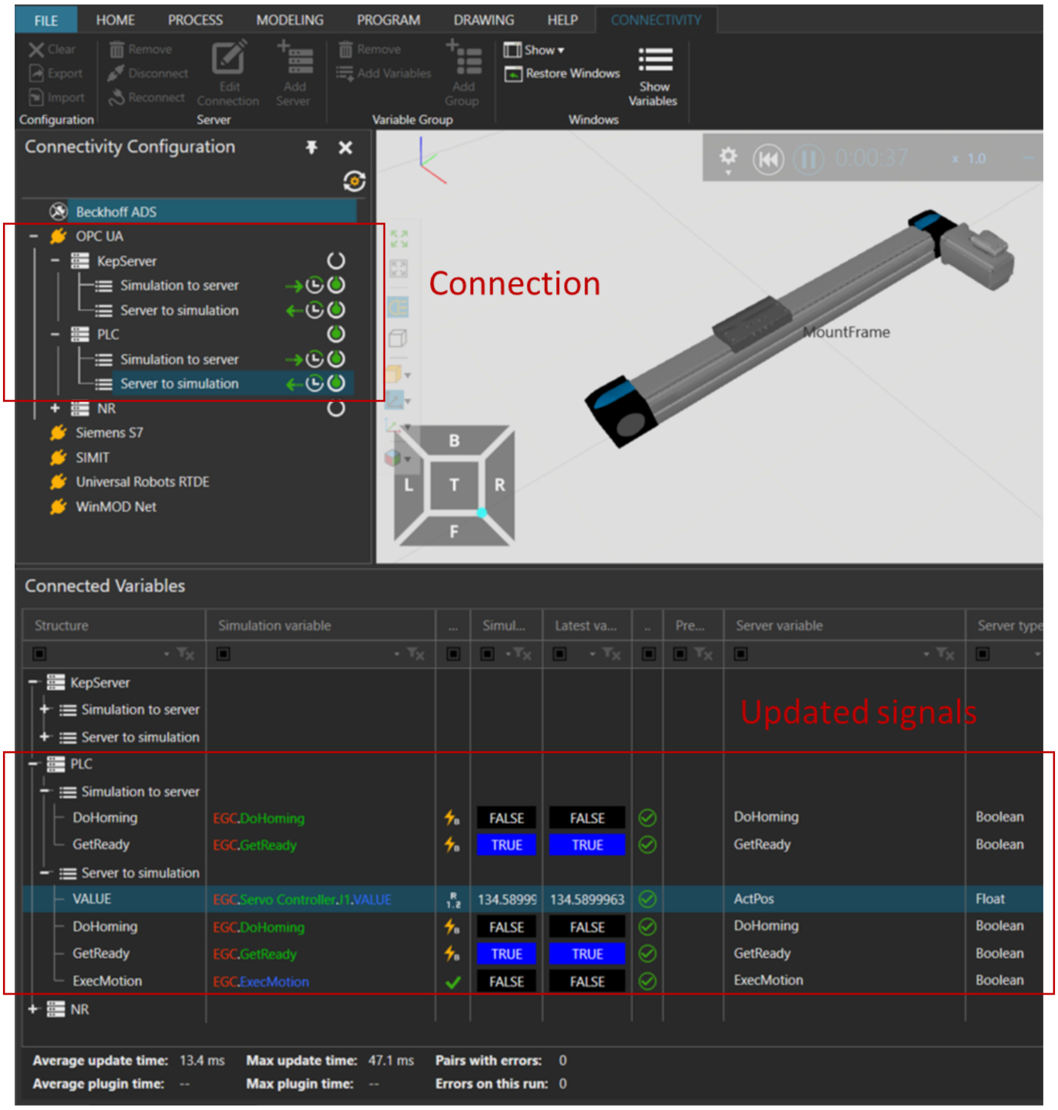


Fig. 7.17: *Establishing connectivity and successful data exchange between PLC and virtual model*

Using the "Connectivity" tab offered in the Visual Components environment, and using the OPC UA communication protocol, mapping of the necessary PLC code signals could be established. A major factor in simplifying this process is Siemens S7 1500 PLC OPC UA connection capability. Otherwise, KepServerEX has to be used in addition to PLC Sim Siemens software.

Figure 7.17 shows the successful exchange of signals (real and logical) between the virtual model and PLC in two paths: "Simulation to server" and "Server to simulation".

As a result, once these signals are changed in either PLC or virtual model, the changed signal is reported its counterpart. In relation to energy consumption prediction, the values inputted into the virtual model and their predicted energy consumption is calculated, which can be transferred into PLC code as new industrial process parameters for example.

With the completion of this phase, it can be said that the digital twin of the component is born. Depending on the estimated energy consumption, the speed of the component can be changed to suit the available amount of energy or to accommodate momentary energy prices.

7.5 Phase III: Connecting external services to the digital twin

7.5.1 Prediction using deep learning as an external service

To increase the benefits of the developed digital twin, further external "services" will be connected so that the system designer can query the outcome of certain design

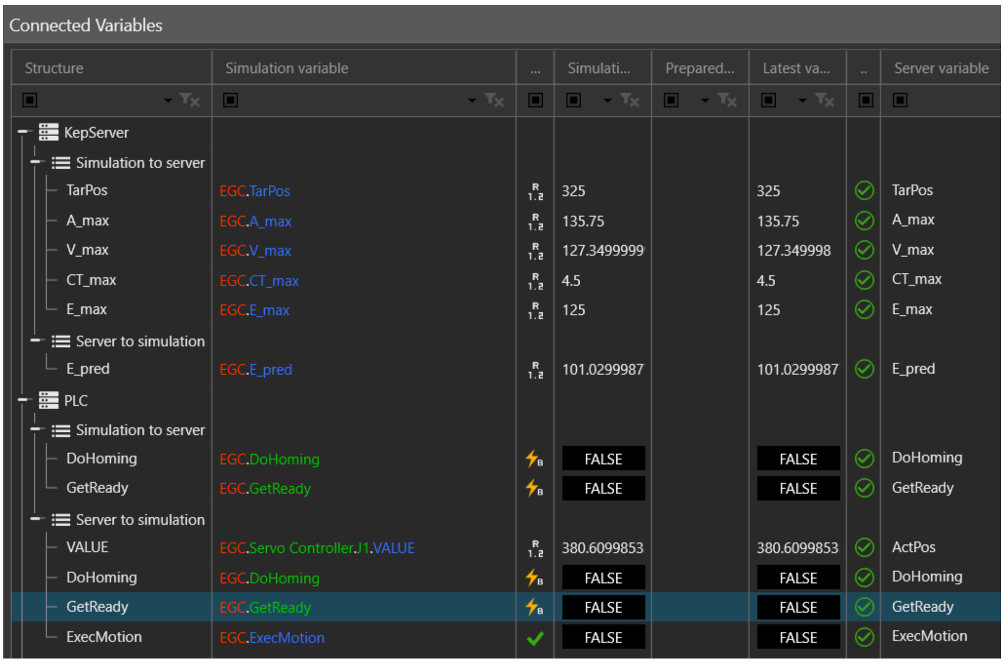


Fig. 7.18: Data exchange between the digital twin and KepserverEX

parameters. It was mentioned earlier that energy consumption prediction using DL was inapplicable in the Visual Components environment. Therefore, it will be shown in this section how to implement DL as an external service. Furthermore, Particle Swarm Optimisation (PSO), is connected to the digital twin.

An essential condition for the successful running of the external services is communication between the digital twin and KepserverEX as shown in Figure 7.18, where OPC UA is utilised in a way similar to that used when connecting to the PLC.

Figure 7.19 shows the graphical code written using Node-RED. Although the coding style is graphical, it includes some functions that are written with JavaScript and other blocks that run external Python scripts.

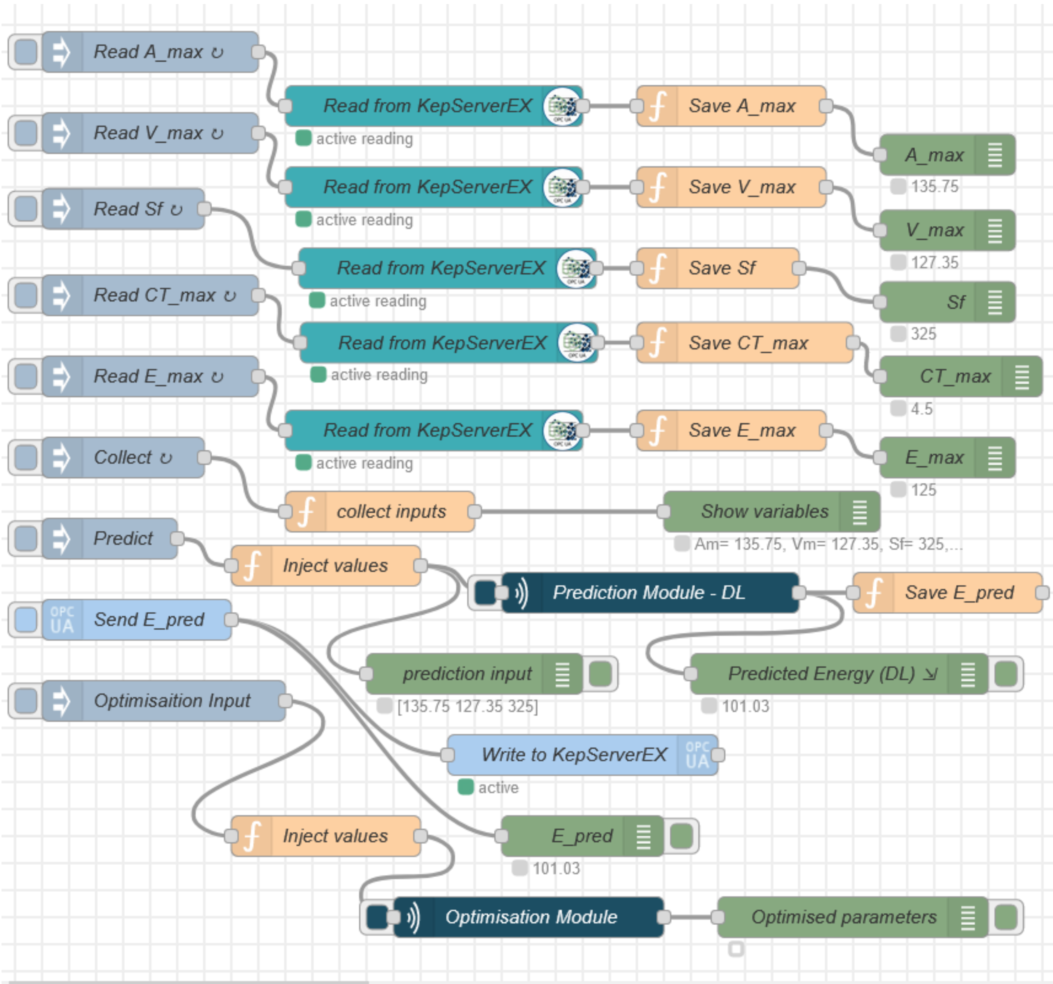


Fig. 7.19: *External services on Node-RED*

The algorithm of the graphical code is as follows:

1. Once there are new parameters of operation, they are passed from the digital twin to KepserverEX.
2. New parameters are read from KepserverEX then collected to form the prediction input vector.
3. Python DL prediction script is run with the provided input.
4. Prediction output is collected and sent to KepserverEX.
5. Prediction output is received on the digital twin.

7.5.2 *Particle Swarm Optimisation (PSO)*

PSO is a biologically inspired algorithm that was introduced by Kennedy and Eberhart in 1995 [Eberhart & Kennedy 1995]. The principle relies on a population of particles each of which has its own position x and its personal best ($xbest$). At the same time, each particle moves towards the global best ($xgbest$) at a specific velocity (Figure 7.20). Hence, the equations that rule particles' movements are [Kaveh 2014]:

$$v_{i,j}^{k+1} = v_{i,j}^{k+1} + c_1 r_1 (xbest_{i,j}^{k} - x_{i,j}^{k}) + c_2 r_2 (xgbest_{j}^{k} - x_{i,j}^{k}) \tag{7–6}$$

$$x_{i,j}^{k+1} = x_{i,j}^{k} + v_{i,j}^{k+1} \tag{7–7}$$

Note that the velocity and position of the particles are different from the motion velocity and position. Similarly, the symbols i, j and k in this section are related only to the particles.

$x_{i,j}^{k+1}, v_{i,j}^{k}$ are the jth component of the ith particle position x and velocity vectors v, respectively, in the kth iteration. r_1, r_2 are two random numbers in the range [0,1] obtained using the Normal Distribution. c_1, c_2 represent the particle's personal cognition and its social behaviour respectively. An inertia term w was added to equation 7–6 to balance the local and global search tendencies of the particles.

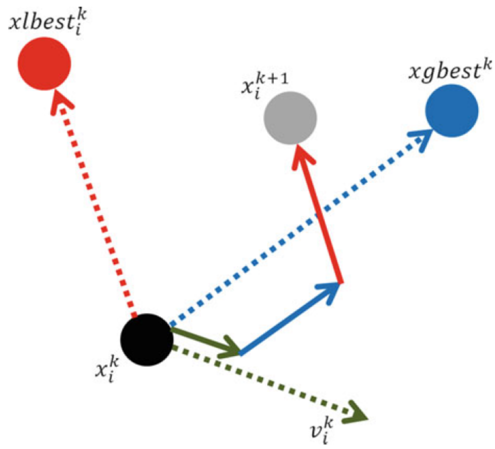


Fig. 7.20: *A schematic movement of a particle in PSO [Kaveh 2014]*

$$v_{i,j}^{k+1} = wv_{i,j}^k + c_1 r_1 (xbest_{i,j}^k - x_{i,j}^k) + c_2 r_2 (xgbest_j^k - x_{i,j}^k) \tag{7–8}$$

Later on, PSO was modified by Clerc [1999] by adding the constriction coefficient (χ) which improves the convergence of the PSO, thus, the formula of velocity vector becomes:

$$v_{i,j}^{k+1} = \chi [v_{i,j}^k + c_1 r_1 (xbest_{i,j}^k - x_{i,j}^k) + c_2 r_2 (xgbest_i^k - x_{i,j}^k)] \tag{7–9}$$

$$\chi = \frac{2}{|2 - \phi - \sqrt{\phi^2 - 4\phi}|};$$

$$\phi = c_1 + c_2, \phi > 4$$

The Particle Swarm Optimisation (PSO) was chosen for optimising the energy consumption due to the following reasons [Kucuk 2017, Rezaee Jordehi & Jasni 2013, Assad et al. 2018]:

- The ability to be used in multi-dimension, discontinuous and non-linear problems.
- Low computational cost.
- Its underlying concepts are simple and easy to code.

- The number of parameters to adjust is fewer compared to other methods.
- It remembers the good solutions resulting from previous iterations.
- The fast convergence of the objective function.
- The final solution is not highly affected by the initial population.

7.5.3 Integration of PSO

The general architecture for integrating external services was introduced earlier in Figure 7.19. Similar to the way prediction using DL was integrated, PSO was programmed in a Python script and integrated. The objective function can be evaluated using the energy value predicted using MLR or DL with the latter being more complex. The mathematical problem can be formulated as follows:

$$
\begin{gathered}
Minimise\ E = f(S_f, A_{max}, V_{max}, CT) \qquad (7\text{–}10)\\
subjected\ to: CT < CT_{lim}\\
A_{max} < A_{lim}\\
V_{max} < V_{lim}\\
where\ CT > 0,\ A_{max} > 0, V_{max} > 0
\end{gathered}
$$

CT_{lim} is the maximum allowed cycle time, and A_{lim}, V_{lim} are motion constraints. E is the value of available energy so that the outcome of PSO can suit energy flexibility requirements.

PSO as a service can be run by the system integrator/designer while integrating the component in a system, or by the digital twin in case of the full automation of decision making.

By the end of this phase, the component designed in Visual Components can be exported as an independent entity with the ability to communicate with external services, and perform energy consumption prediction. Thus, component “reusability” is achieved with a basic Asset Administration Shell (AAS) giving the possibility for future “Plug-and-Produce”.

7.6 Discussion

7.6.1 The support of energy flexibility design

Sustainability and sustainable manufacturing have become urgent requirements. Manufacturing system designers have to respond to this challenge starting from the early design phase of the life cycle. Furthermore, the designed system should make use of smart manufacturing capabilities and comply with the modern design paradigms. To rise to this challenge, and with a focus on energy sustainability in manufacturing automation systems, three research questions and a sequence of the envisioned analysis were suggested as a research methodology.

In relation to the desired interactivity of the manufacturing system, it has been shown empirically that it is possible to mathematically describe the component's energy consumption behaviour, and then to predict it. Components developed in the suggested approach can interact with the control system (PLC in particular), whilst being digital models. In addition, as data exchange is successfully accomplished, some signals in the PLC code can be modified flexibly through the created digital twin. Another significant interaction is with external services. The framework developed in this work can handle further functions once coded as scripts and their inputs are provided and formatted correctly.

In the bigger picture, when components are connected to form a manufacturing cell or an assembly station, total energy consumption can be predicted by aggregating the individual predicted energy consumptions for each of them. Therefore, energy management is achieved by quantifying energy demand. Another dimension of energy management is to assess component's performance based on predefined key performance indicators (KPIs). Then, discrete event simulation can be run to evaluate a certain set of parameters against the proposed KPIs.

For energy flexibility, the proposed approach embeds energy flexibility in components starting from the design phase, unlike the approaches in the literature, which were case-specific. Moreover, the developed components represent cyber-physical components equipped with data processing and communication capabilities. Such mini-scale units can aid strategic planning and decision making when the larger-scale system is built, thus supporting the model-based design by utilising component-based design. When the realisation of such a larger-scale system will require further investment in IoT, big data and cloud applications.

On the design tools development side, for virtual engineering specifically, it is shown that the virtual engineering tool Visual Components could partially support energy consumption prediction. However, with the advancements in information technology, VE tools should be equipped with further computational capabilities. The solution proposed in this work relied on linking external services in order to obtain more accurate predictions. However, relying on one consistent tool to fulfil most of the design requirements can greatly aid system designers and integrators.

The presented work contributes to the growing field of sustainable manufacturing by proactively employing I4.0 technologies to make more flexible components, and thus more flexible manufacturing processes.

7.6.2 Quantification of research objectives

Regarding the practical implications of the implemented experimental work, and in relation to the research objectives declared earlier in Chapter 4:

- As the model of energy consumption is now embedded in the virtual model, the designer of the system can test many possible scenarios (i.e., various velocity, acceleration and position values) in order to have an estimate of the energy flexibility potential. In this manner, energy flexibility turns into a quantifiable parameter that is bounded by the minimum and maximum amounts of consumed energy. Thus, when the manufacturing system is engineered, by using the built energy flexible components, it is possible to estimate the expected energy consumption and its limits, and eventually the flexibility limits. Figure 7.15 shows the amount of the consumed energy in response to the designed motion. Further to the build of this component and exporting it by means of the VE tool (Visual Components in this study), it retains the energy consumption model as a part of its description. Such an introduced capability contributes to the design of machines/manufacturing system (*Research Objective 1*).

- Using the connectivity map (shown earlier in Figure 7.16), the parameters influencing energy consumption are still accessible and modifiable. If the operator (human or machine) intends to modify the maximum velocity, for example, in response to the available energy, submitting the new values via the cyber part results changing them in the physical part. This outcome, on one hand is interpreted as an "interactive" capability (*Research Objective 2*), and on the other hand, it is an enforcement mechanism (*Research Objective 3*) for changing the behaviour of energy consumption. To support this capability, PSO is deployed successfully (Figure 7.19) on the Node-Red platform which means that the operator can run it in order to optimise energy consumption based on the available amount of energy.

-The implemented approach (depicted in Figure 6.4) is inspired by RAMI 4.0 (as declared and explained in the Research Methodology Figure 4.2), thus, it holds the foundations of the compliance with Industry 4.0. The utilised IoT (Node-Red, KepServerEX) and CPS (Visual Components) technologies enabled the successful transfer of data following the digitalisation of the model, which represents the sensible outcome of the *Research Objective 2*. It should be noted that tools used to manage and communicate date are free (Festo FCT, KepServerEX, Node-Red, SQL Server, and Python libraries). VE tools are commercial ones but are an essential element of the cyber-physical systems development means. Some of them are becoming freely available (e.g.,). This significantly eases the implantation of the proposed approach. Running Python codes inside Visual Components might be a speciality of Visual Components, however, in this work, thank to the IoT platform Node-Red, Python codes (e.g. Machine Learning codes) are deployed, then their output is plugged into the virtual model (Figure 7.16).

- Some equipment manufactures (e.g., Siemens and Festo) provide dedicated IoT devices for energy management. Using such devices imposes extra purchasing costs, and 'hides' the energy consumption model as companies are usually reluctant to reveal the properties of their products. The positive side of these devices is that, in theory, they provide a high level of accuracy as the original manufacture has full access to the properties of the manufactured device. In the approach implemented here, the model of energy consumption is established by the designer which grants further customisability and modifiability in terms of handling the inputs and output and their utilisation.

- Modelling energy consumption using machine learning is applicable not only for electric drives (as proved experimentally in this work) but also for other elements/machines, as shown in the author's work on a welding machine. However, ML is not the only method, but an analytical model can replace the ML model. Therefore, other types of elements (e.g., pneumatic, hydraulic) can be similarly modelled then their energy consumption model is embedded in the virtual model.

7.7 Limitations of the prototype

While conducting this research work, some challenges and weaknesses have to be mentioned and taken into consideration:

- The sampling rate of power analyser and KepServerEX: for measuring power, and eventually energy, a power analyser was used. However, it was not possible to obtain reliable data with a sampling rate of less than 100 ms. When doing so, a significant inconsistency between the electrical power and mechanical quantities was found.
- The fixed load for the component: when collecting data to quantify the energy consumption of the studied component (electric drive, motor and axis), the load on the component was fixed. For future studies, the load can be varied and added as a variable in the energy consumption prediction method.
- It was aimed to control energy flexibility through a variety of motion profiles. However, it was not possible to change the motion profile of the drive which is an s-curve.
- The complexity of the communications in the proposed approach: a map of the

communication network utilised in this work was presented earlier (Figure 7.16). However, it is not always easy to connect a variety of servers, clients, services and simulators. Therefore, this communication network has to be simplified in the future in order to reduce the resultant complexity.

- Time and skills economy of the presented approach: in order to successfully create an energy-flexible component, a procedure has been developed and a variety of tools were invested (e.g. virtual engineering, database management, PLC programming, etc.). Additionally, various programming and communication skills were required. Consequently, in industrial practice, users may not possess all the skills needed to follow the procedure in full.

7.8 The practical implementation of the proposed approach

7.8.1 The novelty of the technical work

Linking the energy consumption of electric drives to a corresponding virtual model is not found in the literature as shown in Chapter 3. The current work provided a hands-on guide with a decent level of details on achieving this. As the PLC can access the component's controls via the low level communication channels, this is harnessed to control the component's energy consumption (electric drive), and eventually energy flexibility. PLC's memory is limited, and coding complicated maths on the PLC modules is not recommended, therefore, coding is performed in this work either on the virtual model, or on the Node-Red platform, as the IoT technology helps returning the new parameters to the PLC and to the component afterwards.

Unlike most literature that focuses on understanding the dynamics of the system in order to control energy consumption, using ML in this research simplified this by establishing a link between the process's parameters and the corresponding consumed amount of energy. The DL code is used on the Node-Red platform, however, other ML methods can replace this if they are found to be more suitable. As Node-Red is a pre-built IBM cloud service, this research has shown that the low-level control can be accessed and controlled via cloud services, which in turn can be connected to the rest of the manufacturing system. Doing so, the designer is granted great capabilities, where controlling energy consumption is only one of them.

7.8.2 The means of the technical implementation

The tools used to build an energy-flexible component are representative of their main technologies. For example, Node-Red and KepServerEX are possible tools for utilising the OPC UA communication protocol. Similarly, DL and MLR are commonly used and open-source Python libraries for machine learning which have alternatives in Matlab and Java etc. With the flexibility provided by Node-Red, modules/codes from other software tools can be connected to the virtual models allowing the designer/decision maker to take advantage of their available tools.

A focal point for the successful implementation of the proposed approach is the modelling of energy consumption. Performing this is not strictly limited to machine learning as it has been conducted in this work. Analytical and physical models can replace the ML model as long as their outcome is transferable to the virtual model. For example, the output pf an analytical model written in Matlab can be sent to the IoT platform using Matlab's OPC UA library. However, Matlab does not provide any free toolboxes.

Another important aspect is Visual Components, which is attributed to the Virtual Engineering tools. Such tools are becoming essential for manufacturing systems' developers. There are other alternatives, e.g., the vueOne software developed at the Automation Systems at WMG. The reason Visual Components was chosen is due to its support of Python coding and the simplicity of establishing the connectivity with the PLC and the external entities (e.g. Node-Red). Consequently, any tool capable of providing this may replace Visual Components.

For other types of components, finding the model of the component's energy consumption as a function of the process's parameters, then choosing the suitable method/technology of connecting the outcome of the energy consumption model to the virtual model, enables controlling energy consumption on the way to achieving energy flexibility.

7.8.3 The functional capabilities required for the proposed approach

Integrating components into manufacturing system is challenging and requires a variety of engineering skills. This is especially evident when multiple communication protocols are utilised and the components come from different vendors. Linking this to the proposed approach for developing energy-flexible components, an extra challenge is added on top of the expected challenges. In order to rise to this challenge and facilitate the adoption of the proposed approach, a number of functional capabilities are needed.

The main functional capability required here is modelling in general, and virtual models building in particular. As explained earlier based on RAMI 4.0 model, the transition to the digital world takes place as the digital model is built. In its implementation, this approach relied on modelling energy consumption, and modelling the component in a more inclusive model that makes use of the first one. The former is mainly composed of the model's CAD, however, it acts as a container that accepts a variety of configurations, process models and products. The later can take other forms as explained earlier, however, an appropriate method has to be chosen to make use of the model's output, which reveals the need for another functional capability that is the coordination of communication.

In order to secure the successful exchange and transfer of data, the communication architecture should be well understood. PLC is used in the proposed approach as a data hub to access the low-level component and control its parameters, thus, to control energy consumption. OPC UA communication protocol played an important role in enabling this. On one hand, it supported storing the changes of process parameters over time, which helped to create the energy consumption model. On the other hand, it enabled bridging the virtual model with its physical counterpart. It should be noted that OPC UA is just an example on the communication protocols that support Industry 4.0, and others exist like MQTT (MQ Telemetry Transport) and DDS (Data Distribution Service).

The means of the approach's technical implementation are strongly linked to the required functional capabilities. Therefore, the designer/system integrator has to identify the necessary technologies that can fulfil the required functional capabilities, then take advantage of the corresponding available tools.

Chapter summary

- A three-phase approach is implemented: the physical aspect (Phase I), the cyber aspect (Phase II) and external services (Phase III).
- The utilised physical devices and their integration in order to collect data are explained with the necessary configurations (e.g., PLC, electric drive, power analyser etc.).
- Drive's trajectory is analysed, then, an energy consumption model is created by using machine learning techniques, namely, multiple linear regression (MLR) and Deep Learning (DL). MLR could give good prediction accuracy, whereas DL is more accurate.
- Component's virtual model was created in Visual Components and the communication with KepServerEX and the PLC was established. MLR-based energy prediction was embedded in the virtual model that evolved into a digital twin. Now, the developed component can be reused with its information and communication as an independent system building unit.
- External services such as running deep learning and Particle Swarm Optimisation were added using Node-RED.

Chapter 8

Conclusion and outlook

"I have only made this letter longer because I have not had the time to make it shorter"

— **Blaise Pascal**

As the concerns about climate change grow, the urge to develop sustainable manufacturing becomes prevalent. Solutions developed to contribute to sustainable manufacturing enhancement have to take full advantage of the available technologies. The presented work aimed to address energy flexibility from a cyber-physical systems perspective and in line with the I4.0 paradigm. In the following, the achievement of the research objectives identified in Chapter 1 (1.2.4) and the obtained benefits are summarised.

8.1 Achievement of research objectives

- **Objective 1: To examine the concept of energy flexibility in terms of application means and the targeted control level as means of linking it to manufacturing systems design.**
  A comprehensive review of energy flexibility literature was conducted. Then, a classification of the targeted levels of control was carried out. Following the aforementioned investigation, it was found that energy flexibility management strategies varied from the higher level of ERP to the lowest levels of machine and component, with the latter being of less focused. Furthermore, a recent

trend, known as demand response, - is to correlate the available amount of energy to production planning and control (including scheduling). To cope with this, reactive mechanisms are presented, with the current absence of a holistic design approach. Besides, as a result of the lack of a holistic design vision, the orchestration of lower levels behaviour in response to the changes at higher levels is not currently explained. The approach presented in this work addresses this issue starting from the design phase allowing a deeper understanding of response of the lower levels. Thus, enabling the possibility of judging the suitability of planning scenarios based on their sustainability potential.

- **Objective 2: To make use of ICTs' advancements that led to I4.0. Consequently, to investigate use of the available ICT capabilities in creating proactive and interactive designs.**
  The optimal use of resources (including energy) lies at the heart of I4.0 with a focus on renewable resources. Although research on energy management continues to deploy I4.0 technologies, using those technologies towards energy flexibility is still limited. To overcome this research gap, the presented design takes into account the possibility of using I4.0 technologies, IoT and CPS particularly, thus, component's generated data serve as a means of producing accurate simulation models. Furthermore, the outcome of the simulation, i.e., the virtual model evolves into a digital twin that communicates successfully with both the physical counterpart and an external platform (e.g., cloud, external server). The generated component complies with I4.0 as it has a representation of the physical model, and its own digital representation equipped with possessing prediction and optimisation capabilities. The proactivity of the component is provided through the predicted energy consumption, and its interactivity is provided through its ability to interact with incoming external signals (send/receive data). Thanks to the provided ICTs capabilities, motion control parameters can be changed in real-time based on the model's data stored in the developed energy-flexible component.

- **Objective 3: Supporting system builders and integrators by providing a systematic approach of embedding energy flexibility in manufacturing system design.**
  As mentioned earlier, a major gap in the literature was the absence of a design approach, which hinders including energy flexibility as a design parameter while the system is in the design phase. To achieve this objective and produce a solution that supports the system life cycle, rather than being case-specific, a framework to support sustainable manufacturing based on virtual engineering is developed. The developed virtual models can be reused and recovered across the system's life cycle unlike most of the research work that focuses on the product life cycle. For the selection of building units, a component-based approach is preferred due to the flexibility provided with component design. Moreover, the I4.0 component design methodology is being standardised and the presented approach corresponds to it. The application of the proposed approach is exemplified by an electrical drive where energy consumption is varied using motion control parameters. The same solution methodology can be used for similar components (e.g. pneumatic, hydraulic). Finally, once the obtained data are fed to the digital twin, it acts as a condition monitoring platform, thus, decision making is enabled using the appropriate algorithms Figure 7.16 and Figure 7.19).

8.2 Key research contributions

This research has made the following contributions to the field of sustainable manufacturing from the perspective of manufacturing systems engineering and design:

- An in-depth review of the current status of manufacturing systems' energy flexibility, its application means, and the possible contributions to it. A special focus is given to the control level as it is of great importance when integrating different entities of the sub-systems.
- As the proposed approach relies on data obtained using IoT, it represents a true

smart manufacturing design approach. Furthermore, in-process data could be harnessed for the best use of resources, and could be controlled through the created digital twin.

- The use of motion control and trajectory design for energy flexibility is novel although a lot of work has been done on the energy consumption of motion control applications. Thanks to IoT, it is possible to make timely decisions through real-time access to control motion parameters. Moreover, the model of energy consumption is encapsulated in the design of an I4.0 component.
- In-process data (e.g., maximum velocity and maximum acceleration) are used within a data-based model to predict and control energy consumption. Thus, motion control could empirically contribute to energy flexibility design.
- Manufacturing systems reconfigurability and flexibility constituted important elements of academic research. The current work emphasised their application in smart manufacturing, especially software reconfigurability, and showed the importance of reconfigurability in advancing sustainability under I4.0.
- The solution that is proposed and verified empirically does not require any external vendor-specific hardware or software (e.g., Siemens, Festo, Schneider etc.), but relies on tools that are available for system developers.

8.3 Research benefits

In addition to the academic contributions identified above, there are practical deliverables that can be drawn based on the implemented case study.

- With the widespread use of IoT and its integration into various domestic and industrial applications, its sensors, communication devices and software tools are becoming less expensive than before. Accordingly, using the proposed approach in an industrial environment is now practically applicable.
- The proposed approach is repeatable and can be standardised for various types of components when designing energy-flexible manufacturing systems, especially those with electrical drives. Moreover, the created digital models will facilitate

more sustainable design and reduce development time.

- Thanks to IoT, the created digital twin can be used as a platform for condition monitoring, and then customised depending on the signals to be monitored. For example, maintenance and process analytics.
- Artificial intelligence could be deployed in a collaborative effort with the digital twin. Further, decision making capability based on the PSO algorithm could be added. Therefore, a variety of solutions can be designed using the investigated algorithms.

8.4 Future work

With the successful implementation and the vision of developing sustainable manufacturing systems using virtual engineering and I4.0 technologies, some future work can be built on the concepts and solutions presented in this dissertation. The objectives of the planned future work include but are not limited to:

- **Extending the current work to include further motion control capabilities in order to control energy consumption and increase the potential of energy flexibility.**

  Changing some motion control parameters is proved to be possible using the cyber-physical system and IoT technology. Therefore, based on the built architecture and using the proposed approach, testing a variety of motion curves can add further potential of controlling energy consumption. These added motion curves can be activated by an algorithm deployed on the Node-Red platform.
- **Testing the applicability of the current energy flexibility approach when building manufacturing stations and lines.**

  The current work focused on a motion control component for an improved energy flexibility, which can help building a whole energy-flexible station that is composed of many energy-flexible components. On one hand, this means an extended optimisation space, and on the other hand, more parameters to be configured with their corresponding enforcement mechanisms.

- **Including physical models of the components connected to the cyber-physical system.**
  To overcome the complexity of the physical modelling of both the mechanical and electrical systems of the drive, machine learning is used to estimate energy consumption in the studied drive. For this component (and other types of components), providing their physical models that accurately describe their energy consumption would greatly improve the potential of energy flexibility improvement. Additionally, the “Business” layer in RAMI 4.0 can receive further information.
- **Extending the capabilities of vueOne tool developed by ASG.**
  As the Automation Systems Group at WMG continues to support manufacturers by providing solutions and developing the necessary tools (e.g., vueOne), it is vital to include sustainability in future designs. A future target is to integrate further features in vueOne to support sustainable design, whether economically, environmentally or socially.

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