Ref. Ares(2022)4803886 - 30/06/2022

EnerMan

Energy Efficient Manufacturing System Management

D4.1 - Energy-related Flows and Process Energy Sustainability Modelling, Representation, and Implementation Framework

Date	: 30/06/2022
Deliverable No	: D4.1
Responsible Partner	: SUPM
Dissemination Level	: Public

HORIZON 2020
This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement **No 958478**

EnerMan

Short Description
This deliverable provides a state of the art of relevant models for the EnerMan system and for the implementation of the EnerMan energy aware digital twin. Selected models are able to predict the energy consumption, the energy market price and to define sustainability indicators. The document addresses the relationship between the different models and their formal representation. Preliminary results of the application of some of these models on the CRF bodyshop and on energy market price forecasting are presented.

Project Information	
Project Acronym:	EnerMan
Project Title:	ENERgy-efficient manufacturing system MANagement
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Duration:	36 months

Document Information & Version Management			
Document Title:		D4.1 - Energy-related flows and process energy sustainability modelling, representation and implementation framework	
Document Type:		Report	
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Version	**Date**	**Modified by**	**Comments**
V0.1	17/02/2022	FHOOE, SUPM	Draft ToC
V0.2	13/04/2022	FHOOE, SIMPLAN, SUPM	Part 1 (sections 2., 3.1, 3.3, 4.)
V0.3	22/04/2022	SUPM	Tables, Figures, Equations and references formatting (Part 1)
V0.4	06/05/2022	UNINA, SUPM	Part 1 sec 3.2, ref formatting
V0.5	16/05/2022	FHOOE, SUPM	Writing sec 5.1, Formatting
V0.6	19/05/2022	UNINA	Writing sec 5.3
V0.7	21/05/2022	UOP, SUPM	Sec. 3.4, 5.2, 6.1

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V0.8	25/05/2022	SIMPLAN, SUPM	Writing sec 5.4, introduction and conclusion
V0.9	31/05/2022	UNINA	Editing
V1.0	31/05/2022	AEGIS, STN	Review process
V1.1	17/06/2022	AEGIS, STN	Reviewers' comments addressed
V1.2	28/06/2022	FHOOE, SIMPLAN, SUPM, UNINA, UOP	Final version
V1.3	29/06/2022	SUPM	Submitted version
V1.4	29/06/2022	INTRACT	Format review
V1.5	30/06/2022	Ing. Giuseppe D'Angelo (CRF)	Submitted version

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EXECUTIVE SUMMARY

This deliverable summarises the work that has been carried out as part of Task 4.1 and T4.2 of the EnerMan project. The first part of the document provides an overview of relevant models for the EnerMan system. These models are selected for their capability to monitor and predict the energy consumption, electricity prices and to define sustainability indicators. According to a hierarchical level representation of a production system, the models are defined in a generic way, in order to show their feasibility on the different pilot use cases of EnerMan. Relevant models include physical models (mechanical, electrical, and thermodynamical), statistical and deterministic models, value stream approaches and energy market models. The relationship between the different models is addressed, as well as their formal representation in terms of language and software implementation.

The second part of the document focuses on the implementation and the training of the relevant models in the framework of EnerMan. At the beginning, the procedure of the EnerMan meta-model application is presented. Then, by way of example, a thermodynamical approach is formulated for the CRF bodyshop use case, with reference to available data, sensors and the building plans. The capability of a data fusion algorithm based on the extended Kalman filters to predict wanted indicators, such as the thermal energy consumption and the indoor air temperature, and to deal with uncertainties is addressed. Afterwards, the document focuses on the way to link the use-case requirement with the logical solution, and an optimization algorithm based on artificial neural networks is implemented for the prediction of the daily power consumption of related EnerMan use-cases. Finally, preliminary results about energy market trends based on multivariable input are presented.

This deliverable ends with concluding remarks and shows connections to other EnerMan tasks.

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GLOSSARY OF ACRONYMS

Acronym	Definition
AC	Alternating Current
AHU	Air Handling Unit
API	Application Programming Interfaces
DAM	Day-Ahead Market
DC	Direct Current
EKF	Extended Kalman Filter
ETS	Emissions Trading Scheme
FMI	Functional Mockup Interface
HVAC	Heating Ventilation and Air Conditioning
KPI	Key Performance Indicators
LASSO	Least Absolute Shrinkage and Selection Operator
MAE	Mean Absolute Error
MBSE	Model Based Systems Engineering
MOF	Meta Object Family
OMG	Object Management Group
RC	Resistor–Capacitor
RES	Renewable Energy Sources
RFLP	Requirement, Functional, Logical, Physical
RMSE	Root Mean Squared Error
SMP	System Marginal Prices
SPE	Squared Prediction Error
SPM	Statistical Process Monitoring
SysML	Systems Modelling Language
UML	Unified Modelling Language
VSM	Value Stream Modelling

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1. INTRODUCTION

1.1. Purpose and Scope

This document aims at describing a generic framework for the modelling of energy flows in industrial processes as part of the energy sustainability assessment and improvement.
The work performed and described in this document is mainly structured by the context constraints of the energy durability of factories. The document is organised around each of these constraints and aims at answering any technical issue.

- At the elementary component level, the modelling of energy flows in the industrial process requires models of a large number of components, actuators and energy converters.
- The assembly of these elementary models has to be described and implemented in a common framework and structured in a common flowchart.
- The assembly of these elementary models should be connected in a relatively short loop with information system and fed with sensors and control commands able to:
    - identify specific parameters of the system (by developing an observation system being the least intrusive possible);
    - track variables of the system for different scenario and different control laws (prediction & optimisation);
    - and simulate original scenarios in a prospective point of view for the energy sustainability (simulation engine for alternative approaches).

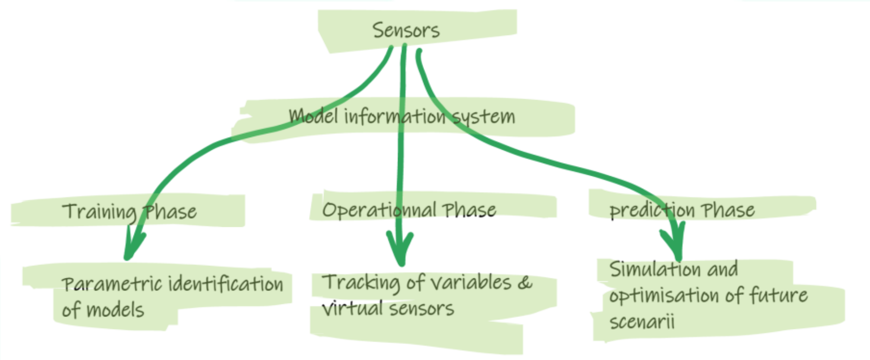

Figure 1. Flowchart of the digital twin.

- The global numerical process has to quantify and respect energy flows in order to identify them accurately for a robust and optimal management of energy and means.
- These objectives of accuracy, optimality and robustness lead to models and methods that could not be only based on deterministic approaches, but have to take into account uncertainties of models, parameters and measurements.

In other terms, this work consists in a generic framework for building the digital twins (Figure 1).
In order to illustrate the proposed methodology, an example referring to the CRF Bodyshop use case of the EnerMan project is provided with details and discussions.

1.2. Structure of the document

The document is organized as follows. Section 2 details the structured collection of the EnerMan related models by presenting their classification, their hierarchical structure, and the template model collection. Section 3 presents an overview of the models relevant for the EnerMan system, with reference to physical models, integrated approaches, statistical and deterministic models, value stream and energy market models. Section 4 focuses on the procedure and languages needed for the implementation of the EnerMan meta-model. Section 5 presents the procedure employed to extract information and create formal model templates and layers. The section continues with the

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implementation of some of the proposed approaches on the CRF bodyshop use-case, with the aim to predict the indoor temperature and the daily power energy consumption. Then, the energy market price forecasting obtained from multivariable inputs is presented. Concluding remarks are reported in Section 6. Appendix A reports a hierarchical level classification and Appendix B the collection of EnerMan related models.

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2. ENERMAN MODEL DESCRIPTION OVERVIEW MODEL

This chapter aims to provide the needed foundation for a structured collection of the EnerMan related models, which can be used by the simulation engine to determine energy related flows and sustainability indicators for a user-defined scenario.

2.1. Description and breakdown analysis

In order to determine the energy related flows, the knowledge of key aspects of the target process is required for the description. Herein the requirements from the targeted production systems, the occurring and scoped energy flows as well as the possibilities to influence are included and will be described afterwards.

The EnerMan model to be developed aims to cover the requirements of the pilots in the best possible way and to enable generalizable usability. In order to obtain concrete requirements, the finalized deliverables D1.1 "SoTA and Analysis of Current Practices" and D1.2 "EnerMan Pilot Requirements and Use Case Specification" were screened to extract requirements and framework conditions of existing industrial production systems. In Table 1 the extracted energy flow relevant requirements for the collection of models can be found.

Table 1 Extracted requirements from preceding deliverables.

Deliverable	Assoc. use case owner	Requirement
D1.1	CRF	Use existing energy management systems
	DPS	Consider already existing sensors (e.g., EpiSensor)
	DPS, AVL	Consider multiple energy levels (e.g., grouped machine monitoring)
	CRF	Building energy management should be considered
	ASAS	Consider own electricity generation from primary energy sources
	STN	Ability for day-ahead predictions
	CRF	Consider existing KPIs
	IFAG	Consider CO_2 ontology on supply chain level
	AVL	Consider energy generation from recuperation
D1.2	CRF	Scalability of the model/solution
	IFAG	Integration of HVAC and chillers, environmental conditions
	ASAS	Consider multiple energy sources

In the scope of the EnerMan project multiple types of energy and resources are considered. A pilot survey conducted within the project revealed that (1) electrical energy, (2) natural gas, (3) industrial water and (4) thermal energy should explicitly be considered. As these types differ in storability, price volatility and composition, a general formal model is sought in order to compose the general formal model.

An example of the volatility of energy parameters is visualized afterwards in Figure 2. In the figure, the wholesale price of electricity as well as the resulting CO_2 equivalent emissions can be found. We observe that not only energy efficiency matters, but also the timespan in which energy is consumed is important for energy sustainability. The saving potentials of shifted energy consumption are covered by energy flexible measures and will likely gain more relevance in the upcoming years by the expansion of inherently volatile renewable energy sources. Notably, there is a correlation between inherent CO_2 equivalent emissions and wholesale price of electricity due to the energy mix being used to meet the projected electricity demand based on the market-clearing procedure employed by market operators. In the long term therefore cost savings statistically result in emission savings and vice versa.

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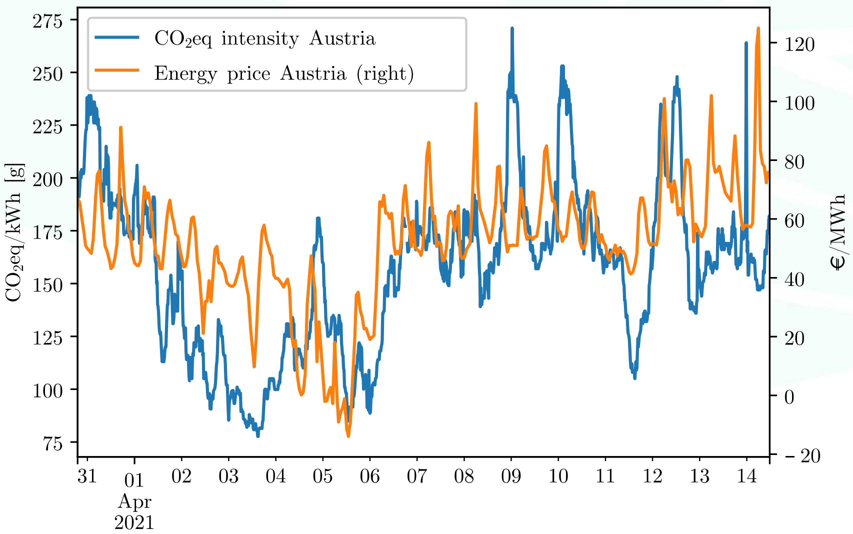

Figure 2. Electricity wholesale price and associated carbon emissions for Austria Sources: Entso-E (wholesale price), Co2signal (CO_2 equivalent emissions).

Considering the actual production processes a distinction can be made between two general manufacturing process types among pilot use cases: discrete and continuous. The result of discrete production processes is an integer number of products or pieces as opposed to the floating-point value of continuous processes.
The manufacturing process type is largely responsible for how energy consumption can be influenced. In continuous processes, the change of the production sequence (scheduling) as well as order allocation in case of several available machines (routing) is not possible and the focus is on the optimization of the process parameters. With discrete processes, on the other hand, there are additional possibilities to influence. Graßl [1] provides a list of the possibilities to influence, as shown in Figure 3. Notably, the applicability of the individual measures depends on the individual use case and conditions.

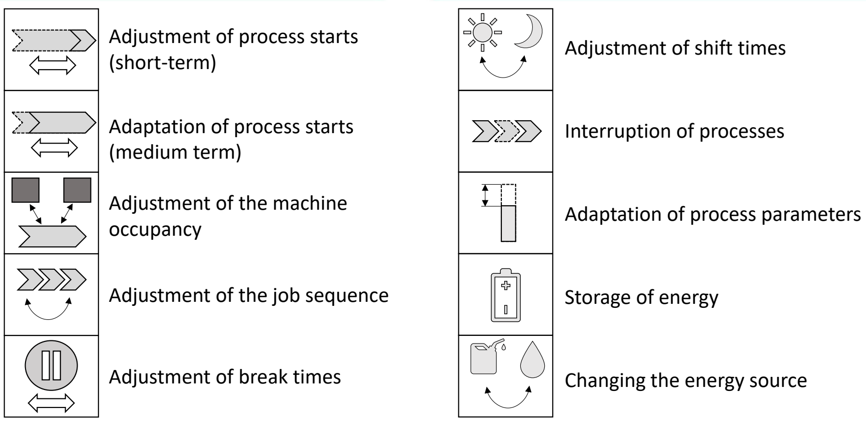

Figure 3. Energy flexible possibilities to influence the energy consumption of manufacturing processes [1].

2.2. Classification of models

In order to make a predictable statement of energy consumption, the production system must be modelled for future state predictions. There is a wide range of applicable models that use different objectives of considered domains, accuracy, and underlying principle. A representation of this topic can be made by the "zoo of models" [2]. One challenge of the EnerMan simulation engine is to create

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an information exchange between different model types to create a compromise between high accuracy and performance in line with real word sensory data.
In the context of manufacturing, there are a number of important factors to be considered which are often interrelated. For example, a high model fidelity and prediction accuracy is generally coupled with an increased modelling effort. The variety of models must also be taken into account. Models are often aimed at different levels of abstraction, depending on the statement to be made. The level of abstraction is mostly related to the hierarchical levels of the production. The system levels defined for EnerMan will be analysed in more detail in the following sections, as they play a central role in the inherent energy allocation in products.

2.3. Hierarchical structure

In order to achieve a classification for energy allocation, the EnerMan considered production system must be divided into hierarchical levels. For this purpose, reference points from various international standards and scientific literature, [3, 4, 5, 6, 7, 8, 9, 10], were researched. The literature was chosen to represent a flexible and sustainable manufacturing system with aspects on material or information flow, hierarchical structuring as well as process modelling. The list of extracted levels can be found in the appendix. As the levels and naming conventions differ between the found reference points a merge was proposed. The merge aimed to maximize congruent reference points while minimizing needed levels. Thus, the levels relevant to EnerMan are a composition of these sources and were identified as follows, [11]:

1. Value chain
2. Plant
3. Workshop area
4. Machine
5. Aggregate
6. Component

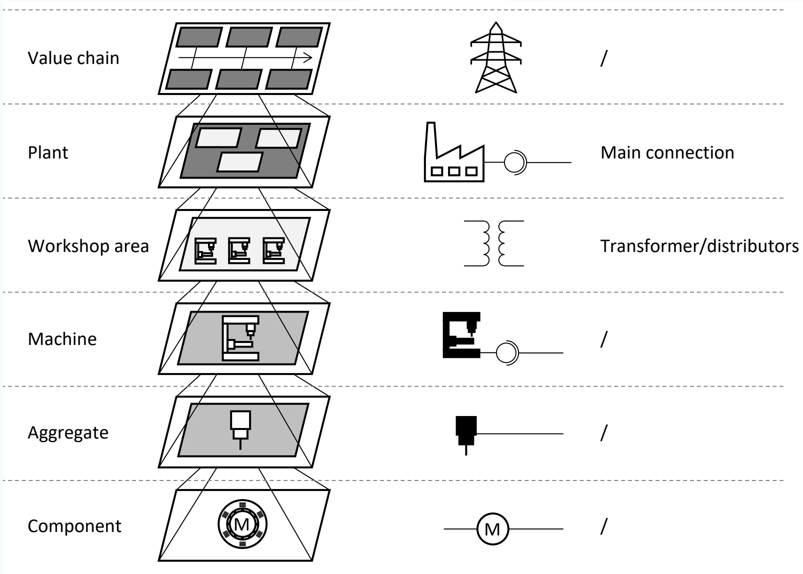

Figure 4. Hierarchical versus electrotechnical levels within manufacturing environment (adapted from Liebl [11]).

One difficulty in energy flow allocation is the missing possibility to allocate consumed energy based on the production-internal energy distribution network as pointed out by Liebl. Although the energy distribution network can also be classified into hierarchical levels, the structure may not be aligned with zones. Furthermore, from machine level downwards, allocation is no longer possible through the distribution system, and it must be allocated as far as possible by means of sensors and a detection and allocation logic. Figure 4 visualizes the electricity distribution network contrary to the hierarchical

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structure. It is implied, additional sensing and energy flow tracing is required to the existing distribution sensors, [11].
The considered EnerMan hierarchical levels serve a purpose in the model reduction, as well as in the detailing of models.

2.4. Template model collection

Given the explained characteristics, the given pilot case requirements and the classification of the models, a collection of models is created in the sense of the "zoo of models", which serve as a basis for the formal model creation. Based on the defined criteria, selected model types that are particularly relevant for EnerMan are explained in the following section. The entirety of the collected models, including a brief description, can be found in the appendix.
The models included in the template model collection were collected with the aim to create an abstract set of models for a later interconnection. The interconnection is strongly coupled with the models information inputs and outputs. The input of an individual model is therefore the output of another model or set of models and vice versa. Thus, a possible chain of models can be derived by the definition of desired information output.
Additionally, the models can be described and classified by inherent attributes, such as the model type or the relevant hierarchical level. Another important criterion is the scope of validity. The scope of model validity represents a constraint by neglecting physical domains or by the addition of simplifications. These simplifications usually result in a reduced modelling effort but also lower model fidelity. Therefore, the application of such models must be also suitable for the needed information output. The resulting collection shall therefore represent the models for interconnection as visualized in the concept in Figure 5.

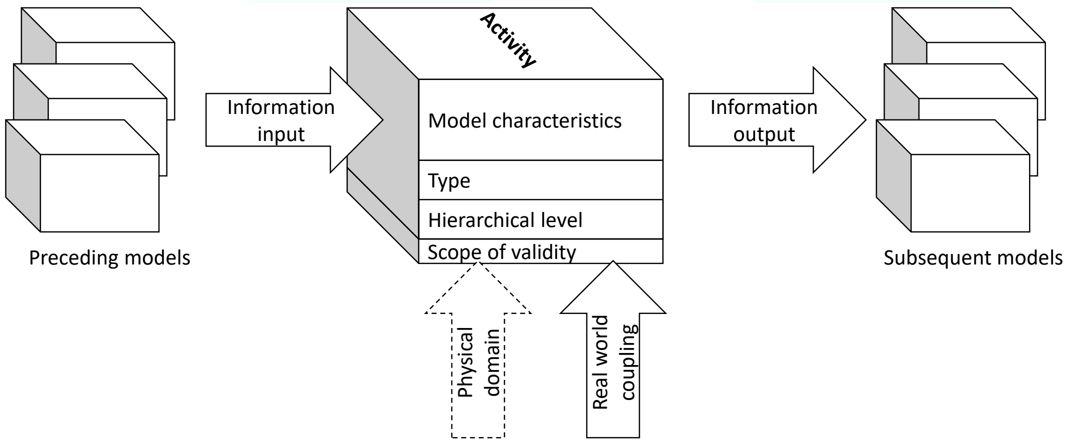

Figure 5. Model properties and input/outputs in the model collection template.

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3. ENERMAN RELEVANT MODELS

3.1. Physical Models

This section is devoted to the description of the physics-based models of the equipment widely used in industrial applications. The main objective of these models is to accurately quantify and predict the electrical energy consumption. The systems taken into account relate to the low-level of the whole industrial plant, namely components and machineries, and cover several physical domains, such as mechanics, dynamics, electrodynamics, fluid dynamics and thermodynamics.
The proposed modelization relies on the following assumption: attributes and energies of the spatially distributed physical systems are localized into discrete elements. This simplification leads to lumped-parameter models, [12] [13], whose analytical formulation consists of sets of ordinary differential equations and algebraic equations describing the relationships between the physical variables involved. In such equations, physical properties are expressed by parameters which can be time-invariant or time-variant, known or unknown. The main variables are usually classified in potential variables and flow variables (Table 2).

Table 2. Potential and flow variables for different physical domains.

Domain	***Mechanical***	***Electrical***	***Hydraulic***	***Thermal***
Potential variable	Position / Angular position	Voltage	Pressure	Temperature
Flow variable	Force / Torque	Current	Mass flow	Heat flux

According to the nature of the system, the resulting equations can be linear or non-linear. The proposed models, also called dynamic models, enable to analyze the behaviour of the systems during transient processes and in steady-state regime.
Nowadays, for both industrial and academic usage, there are numerous software and tools for modelling and simulating of complex physical systems, see for example: OpenModelica[1] (open source), Dymola[2] (developed by Dassault Systèmes and based on the Modelica language), Simscape[3] (developed by MathWorks within the Simulink environment), Simpack[4] (developed by Dassault Systèmes), PSIM[5] (developed by Powersim), etc. By extracting the libraries implemented in such softwares, a quite exhaustive list of industrial components, devices and machines is obtained, such as

- ***rotational and translational mechanical systems*** (mechanical power transmission, i.e., motion transmission): springs, shafts, joints, belts, chains, pulleys, spur/helical gear trains, planetary gear trains, worm/bevel gears, screw-nut systems, ball screws, rack-pinion systems, etc.
- ***electrical systems*** (electrical power generation, transmission, and conversion): resistors, capacitors, batteries, inductors, solenoids, voltage/current sources, switches, semiconductors (diodes, transistors, thyristors, etc.), converters, rectifiers, inverters, transformers, generators and motors (DC/AC, synchronous/asynchronous, single/three-phase), etc.
- ***fluid systems***, analysed both from the hydraulic and thermal point of view: tanks, vessels, pipes, valves, actuators, centrifugal/positive-displacement pumps and compressors, hydraulic/wind turbines, gas/steam turbines, fans, heating/cooling systems (boilers, chillers, etc.), heat exchangers, humidifiers, air conditioning systems, etc.

[1] https://www.openmodelica.org/
[2] https://www.3ds.com/products-services/catia/products/dymola/
[3] https://www.mathworks.com/products/simscape.html
[4] https://www.3ds.com/products-services/simulia/products/simpack/
[5] https://powersimtech.com/products/psim/capabilities-applications/

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The analytical models can be formulated by referring to the literature of the specific physical domain, or by finding information in the documentation of the specific software (if accessible). By way of example, the model of a complex system, including a DC motor, a power transmission, and a generic load, is described, both from the electro-mechanical and thermal point of view.

3.1.1. Electrical subsystem: DC motor modelling

A brushed DC electric motor takes electrical energy from power source, performs electromechanical conversion, and delivers mechanical work to the output shaft. DC electrical machines consist of the stator magnetic circuit, the rotor magnetic circuit and the rotor winding, also called armature winding. The stator magnetic flux is created either by DC currents in the excitation winding or by permanent magnets and propagates passing through the rotor. The DC current reaches the rotor conductors by means of a mechanical commutator, which consists of a rotating collector and two fixed carbon brushes. Each rotor conductor is subjected to the electromagnetic force arising from the interaction with the magnetic field. All these forces generate a mechanical torque that acts on the rotor and generates motion. When the rotor winding rotates in the magnetic field, an electromotive force is induced in it. The electromotive force is such that it opposes the cause which produces it, i.e., the voltage source.

The analytical model here adopted, see [13], is based on two differential equations of voltage balance in the windings, and on two algebraic relations describing the electromagnetic torque and the electromotive force. The process of modelling includes the following approximations: iron losses in magnetic circuit are neglected; nonlinearity of magnetic circuit is neglected (there is no magnetic saturation); parasitic capacitances are neglected. In DC machines the mutual inductance between the excitation winding and the armature winding is equal to zero, [13]. Hence, the differential equations describing the changes of the excitation current i_e and the armature current i_a are decoupled.

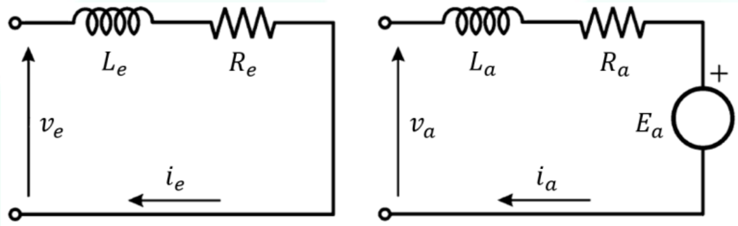

Figure 6. Equivalent circuit of the excitation winding (left) and the armature winding (right), from [13].

The voltage source v_e feeds the excitation winding and the source v_a feeds the armature winding. The excitation winding has electrical resistance R_e and self-inductance L_e. The equivalent internal resistance of armature winding R_a includes the resistance of the rotor conductors and the resistance of the commutator (brushes and collector). In addition to the resistance, the rotor circuit has self-inductance L_a and induced electromotive force E_a. The equivalent circuits of the windings are depicted in Figure 6 and the two voltage balance equations are:

$$v_e = R_e i_e + L_e \frac{di_e}{dt} \qquad v_a = R_a i_a + L_a \frac{di_a}{dt} + E_a \tag{1}$$

In practice, the total resistance in the armature circuit is higher than R_a, because the power supply has an internal resistance, as well as the conductors connecting the supply to the brushes. Furthermore, the armature circuit may have a resistor inserted in series with the purpose of reducing the initial current and initial torque. In steady-state conditions, there are no changes in the rotor speed nor in electrical currents in the windings, then the voltage balance equations become:

$$V_e = R_e I_e \qquad V_a = R_a I_a + E_a \tag{2}$$

The model also includes the expressions for the induced electromotive force E_a and the electromagnetic torque T_{em}, which are proportional to the angular speed of the rotor ω_m and the armature current i_a, respectively. As demonstrated in [13]:

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$$E_a = k_E \omega_m \qquad T_{em} = k_T i_a \tag{3}$$

The proportionality constants depend on several machine parameters, such as the number of rotor conductors, the number of magnetic poles and the excitation flux.
If the excitation flux is generated by permanent magnets, the DC machine does not have an excitation winding and the analytical model is obtained by omitting the corresponding differential equation.
DC motors are often used to control the forward and backward motion of mechanical parts, involving the rotor speed in both directions. Since the sign of the voltage v_a is determined by the direction of the rotor speed, the armature power supply should provide voltages of both polarities. A solution which satisfies this need is the bridge with four switches (see Figure 7). A positive voltage v_a is obtained by turning on the switches S1 and S4, while a negative voltage v_a is given by turning on the switches S2 and S3. DC machines often receive electrical energy from single-phase or three-phase AC power grid. In these cases, it is necessary to use a rectifier which converts AC voltage in DC voltage: the output DC voltage is proportional to the rms value of the input AC voltage. Rectifiers (Figure 7) are static power converters comprising diodes or other semiconductor power switches. Bridges and rectifiers introduce nonlinearities in the equations of the dynamic model.

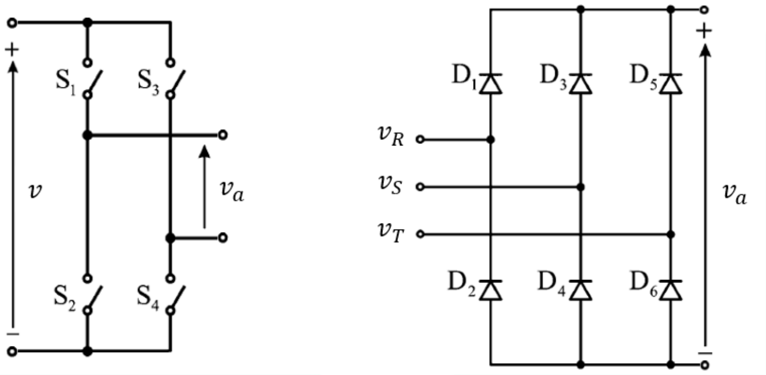

Figure 7. Bridge with switches for inversion of the voltage polarity (left) and three-phase AC rectifier with diodes.

3.1.2. Mechanical subsystem: power transmission modelling

Many power generating machines, such as internal combustion engines and electric motors produce power in the form of rotary motion. Motion can be transmitted directly or through intermediary components. The torque-speed characteristics of prime movers depend on their type and size, but these characteristics may not match those of a given application or load. Several mechanical devices can be used to transform the torque-speed characteristic of a motor to a useful output characteristic and gear trains are the most common solution, [14] and [15].
Electric motors deliver the driving torque to work machines by means of the mechanical coupling at the rotor shaft. In addition to modelling the electrical subsystem, it is necessary to model the mechanical subsystem and derive the differential equations describing changes in the rotor speed.
The analytical model is developed for the torsional vibration analysis of a mechanical subsystem consisting of the following elements (Figure 8): the rotor of the DC motor, the input shaft (rotor shaft), a single stage gearbox (a pair of gears, driver and driven member), the output shaft and the load.

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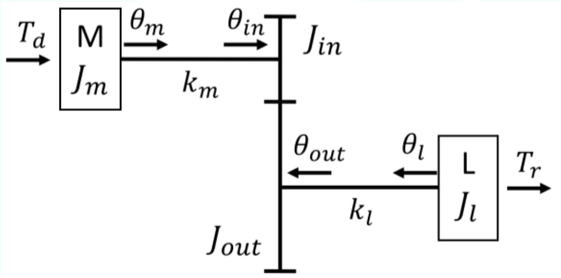

Figure 8. Mechanical power transmission system: motor, gearbox and load.

The transmission ratio of the gearbox is $\tau = \omega_{out}/\omega_{in}$, where ω_{out} is the angular speed of the driven wheel and ω_{in} is the angular speed of the pinion. Power losses in gear systems are mainly associated with tooth friction, which is related to the gear size, the transmission ratio, the pressure angle, and the friction coefficient. The efficiency η of a gear system is calculated as the ratio between the output shaft power P_{out} and the input shaft power P_{in}:

$$\eta = \frac{P_{out}}{P_{in}} = \frac{T_{out}\omega_{out}}{T_{in}\omega_{in}} = \frac{T_{out}}{T_{in}}\tau \tag{4}$$

The output torque T_{out} and the input torque T_{in} of the gearbox are linked by means τ and η. Under normal conditions of lubrication, the efficiency per stage is about 98%, thus it is assumed $\eta \cong 1$.
The mass moments of inertia of the motor, the two gears and the load are J_m, J_{in}, J_{out} and J_l, respectively; the inertia of the shafts is negligible. The torsional stiffnesses of the input shaft and the output shaft are k_m and k_l, respectively. The degrees of freedom of the system are the rotation of the motor θ_m, the rotation of the pinion θ_{in}, the rotation of the driven gear θ_{out} and the rotation of the load θ_l. If no allowance is taken for backlash (it would introduce nonlinearities) and the deformation of gear wheels is negligible, it is possible to reduce the number of degrees of freedom by introducing $\theta_{out} = \tau\theta_{in}$, [16].
Since iron losses are neglected in the electrical model, the drive torque T_m coincides with the electromagnetic torque T_{em} generated by the DC motor. A positive value of T_m leads to an increase of the rotor speed. The load torque T_l represents the mechanical load of the work machine which resists movement. A positive value of T_l causes the rotor speed to decrease.
The analytical model includes three equations of motion, which describe the dynamic behaviour of the mechanical subsystem in terms of displacements, velocities, and accelerations. The equations of motion can be obtained from the free body diagram of each element by studying the rotational equilibrium or through an energetic approach by applying the Lagrange method, [12] and [16]. The two procedures lead to the same result:

$$\begin{bmatrix} J_m & 0 & 0 \\ 0 & J_b & 0 \\ 0 & 0 & J_g \end{bmatrix} \begin{Bmatrix} \ddot{\theta}_m \\ \ddot{\theta}_{in} \\ \ddot{\theta}_g \end{Bmatrix} + \begin{bmatrix} c_m & -c_m & 0 \\ -c_m & c_m + \tau^2 c_g & -\tau c_g \\ 0 & -\tau c_g & c_g \end{bmatrix} \begin{Bmatrix} \dot{\theta}_m \\ \dot{\theta}_{in} \\ \dot{\theta}_g \end{Bmatrix} + \begin{bmatrix} k_m & -k_m & 0 \\ -k_m & k_m + \tau^2 k_g & -\tau k_g \\ 0 & -\tau k_g & k_g \end{bmatrix} \begin{Bmatrix} \theta_m \\ \theta_{in} \\ \theta_g \end{Bmatrix} = \begin{Bmatrix} T_d \\ 0 \\ -T_r \end{Bmatrix} \tag{5}$$

$$[M]\{\ddot{\theta}\} + [C]\{\dot{\theta}\} + [K]\{\theta\} = \{T\}$$

where $J_b = J_{in} + \tau^2 J_{out}$ and $[M]$, $[C]$ and $[K]$ are the mass, the damping, and the stiffness matrix, respectively. The main causes of energy dissipation are the friction in bearings and the air resistance experienced by the rotating parts. Since these mechanical losses are usually small, it is not of interest to introduce complex models, so the friction torque is considered proportional to the speed, [13]. The damping matrix $[C]$ is computed by introducing the approximation of a stiffness proportional viscous damping, with $[C] = \beta[K]$.

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3.1.3. Thermodynamic subsystem: power flow and losses

In order to better understand the process of energy conversion and energy consumption, it is required to study the power flow and the power losses in the whole system. The power balance equation is derived by considering that the machine operates in steady-state conditions, [13].

The electrical sources, which feed the excitation and armature windings, supply the electrical power P_{el} to the DC motor. Part of this power is dissipated in the windings due to copper losses P_{C_u} (iron losses are neglected). In addition, the power P_f is spent to overcome mechanical losses due to rotation, namely friction in bearings and air friction. These powers are calculated as follows:

$$P_{el} = V_e I_e + V_a I_a \qquad P_{C_u} = R_e I_e^2 + R_a I_a^2 \qquad P_f = \{\dot{\theta}\}^T [C] \{\dot{\theta}\} \tag{6}$$

The mechanical power P_m delivered to the load is computed thanks to the power balance:

$$P_{el} = P_{C_u} + P_f + P_m \;\; \rightarrow \;\; P_m = P_{el} - P_{C_u} - P_f \tag{7}$$

Power losses (P_{C_u} and P_f) are converted into heat by the Joule effect and this cause an increase in the system temperature. If this temperature exceeds the temperature of the environment, the heat is transferred to the environment and the system is cooled. The temperature remains constant if the heat generation is in equilibrium with the heat emission. The power of heat emission (cooling power) is $\Delta T / R_T$, where ΔT is the temperature difference with respect to the environment and R_T (°C/W) is the equivalent thermal resistance of the system. The change of the system temperature is described by the following differential equation, [13] and [17]:

$$P_{C_u} + P_f - \frac{\Delta T}{R_T} = C_T \frac{d(\Delta T)}{dt} \tag{8}$$

where the right-hand side represents the rate of the heat accumulation within the system and C_T (J/°C) is its equivalent thermal capacity. The equation is derived by assuming that all the components of the system have the same temperature. The implementation of a thermodynamical model on the CRF bodyshop use-case will be discussed in section 5.2.

3.2. Integrated models for system description and analysis

Reaching energy sustainability of existing production systems and guaranteeing energy-consumption awareness is a wide and complex issue to address. Several interrelated elements and processes that have no common management need to be taken into account. Therefore, Section 3.2.1 presents the Requirement, Functional, Logical, Physical (RFLP) approach that is useful to manage model relationships while ensuring requirements traceability; Sections 3.2.2 and 3.2.3 present statistical models and deterministic models that are pivotal to reach EnerMan goals, respectively.

3.2.1. RFLP approach for system description and analysis

Model Based Systems Engineering (MBSE) is a suitable methodology to reach energy sustainability and guarantee energy-consumption awareness, [18, 19], as it allows managing the growing complexity of systems, maintaining consistency, and assuring requirements traceability during system development. MBSE is the formalized application of modelling to support system requirements, design, analysis, verification, and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases, [20].

The Requirement, Functional, Logical, Physical (RFLP) approach is a structured approach enabling MBSE methodology that is very useful to allocate requirements, needs and constraints, and to select key performance indicators to be assessed with reference to energy consumption, energy costs, and environment footprint. The method consists of four specific phases: (I) Requirements engineering, (II) Functional design, (III) Logical design and (IV) Physical design — RFLP. By applying a dedicated methodology and tool integration, the whole RFLP approach can be implemented in MATLAB®

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environment. Each step is carried out by using, in a specialised way, a toolbox of the same software (i.e., Simulink Requirements, System Composer, Simscape/Simulink, Simscape Multibody). This means that all information can be systematically organized by different levels of detail, centralized and exchangeable. More specifically, each phase provides one or more models as output: (i) Requirement engineering phase defines and hierarchically organizes systems requirements according to their nature into various categories, e.g., functional, operational, safety, maintainability, performance, etc.; (ii) Functional design phase defines the functional architecture model of the system. According to a top-down approach, functions and sub-functions of the system are defined and the relations among them are defined in terms of energy, material, or signal links; (iii) Logical design phase defines the logical architecture model of the system: system components and sub-components are defined at a higher level of abstraction and hierarchically organized according to a top-down approach. Behavioural models are generated from logical blocks; (iv) Physical design generates physical models from logical blocks and their interfaces. Each physical components is described by a set of mathematical equations in order to accomplish multi-domain modelling and simulation of energy flows.

Considering the EnerMan context, this model-based approach enables managing both system behaviour and requirement fulfilment by means of an iterative process that allows establishing and tracing the relations among the different models that are systematically organized in a hierarchical framework. Requirement traceability is guaranteed through two-way links between models.

3.2.2. Interpretable predictive models and statistical process monitoring

In the Industry 4.0 framework, the experimental measurements of a quality characteristic such as the energy consumption are often characterized by complex and high dimensional formats that can be well represented as functional data or profiles, [21]. There are two main objectives when using statistical models for this type of data in the EnerMan project. The first one is the prediction of the energy consumption profiles through regression models as a function of covariates, the second one is statistical process monitoring (SPM) of profiles to quickly detect unusual conditions in the process when special causes of variation act on the energy consumption.

To predict energy consumption profiles, the generalization of the multivariate regression analysis to the case where the predictor and/or the response have a functional form is referred to as functional regression and is illustrated e.g., in [22]. Functional regression models can be grouped in models with scalar response and functional predictors (scalar-on-function regression, [23]), models with functional response and scalar predictors (function-on-scalar regression), and models where both the response and the predictor are functions (function-on-function regression, [24]). The main advantage of these models is their suitability for dealing with high-dimensional data observed on possibly uneven, non-equidistant time points, with noise. The most common functional regression models are linear and are very useful because they are able to model complex data while still being interpretable, because the functional regression coefficients provide the influence of covariates on the output quantity of interest. Alternative regression models that go beyond linearity but still preserve interpretability have been introduced in the literature such as functional additive models, [25, 26].

The second aim of the statistical models is the SPM of energy consumption profiles. When special causes of variation acting on the energy consumption are identified by such models, the process is said to be out-of-control. On the contrary, when only common causes are present, the process is said to be in-control. The simplest approach for monitoring one or multiple functional variables is based on the extraction of scalar features from each profile, e.g., the mean, followed by the application of classical SPM techniques for multivariate data [27]. However, feature extraction is known to be problem-specific, arbitrary, and risks compressing useful information. Thus, there is a growing interest in profile monitoring, [28], whose aim is to monitor a process when the quality characteristic is best characterized by one or multiple profiles. Some recent examples of profile monitoring applications can be found in [23] and [24].

The two aforementioned objectives, i.e., regression and SPM, can be pursued at the same time through the so-called regression control charts, [29], introduced in the functional data analysis context

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by [24]. Once a predictive regression model has been built on the quality characteristic of interest chosen as the response variable, then the control chart built on the residuals of the regression model is more powerful in the detection of shifts. Clustering of profiles, also known as functional clustering, can also help in the detection of anomalies. Clusters can be used to identify the most critical groups in the data, if they exist, so that SPM can be focused only on such groups, as has been done in the automotive manufacturing industry by [30].

3.2.3. Deterministic models

Deterministic (white box) models are developed and used in EnerMan research activities to train the digital twins (black box models) for the assessment of energy performance and environmental footprint, as well as for the application of model predictive control frameworks. Accordingly, the implementation of such models is pivotal for the following targets:

- Predicting **Key Performance Indicators (KPIs)** related to energy consumption, energy costs, and environmental footprint;
- Filling missing (change wrong) data collected by measurements/to enlarge the data acquisition horizon for training at early stage;
- Finding a physical link between the controlled **variables** and **boundary conditions** to the **KPIs**;
- Checking the consistency of **Digital Twins** with models' predictions;
- Extending the analysis from the case to new **scenarios**, *e.g., **i)*** variable energy prices, ***ii)*** variable climate conditions, ***iii)*** changed energy flows, ***iv)*** implementation of energy efficiency measures.

3.3. Value Stream modelling approach

This section provides a brief overview on the state-of-the-are of value stream modelling (VSM) and value stream simulation and the innovations envisaged for VSM in the context of the EnerMan project. The extended VSM approach is implemented as part of the Simulation Engine in Task T4.3. Details about it are available in deliverable D4.2 "Simulation approach/mechanism for providing energy related indicators".

3.3.1. Value Stream modelling overview

Value stream modelling and value stream simulation are well established, [31]. Value stream mapping includes value stream analysis, value stream design, value stream simulation, and value stream planning (Figure 9).

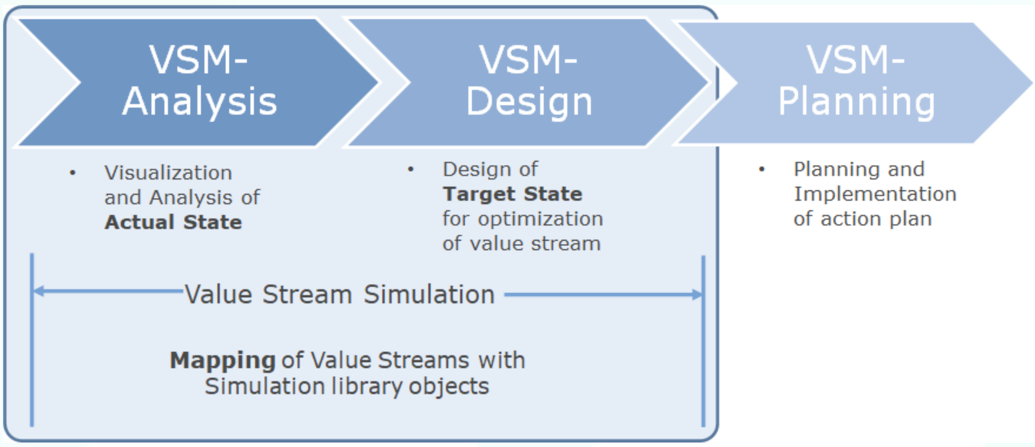

Figure 9. Steps in value stream mapping (VSM)

The methodology itself dates back to 1999 and was initially described by Rother and Shook, [32]. It employs a set objects on an aggregated functionality level to describe production flow and identify stock levels, processes, process times etc. (Figure 10).

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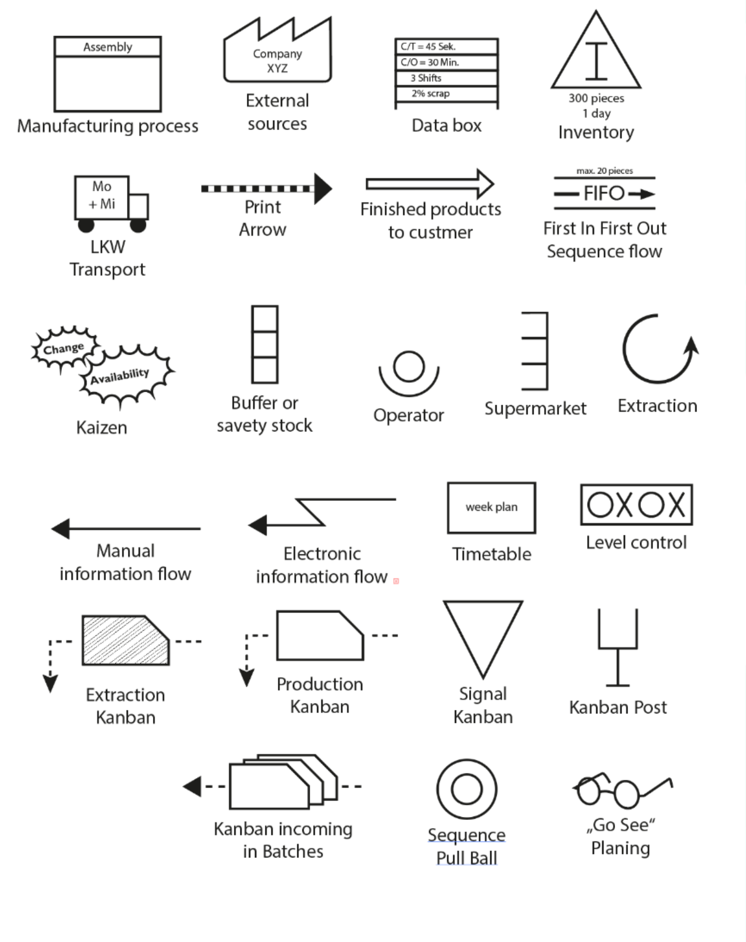

Figure 10. Icons used in value stream mapping (Rother and Shook 1999).

Figure 11 is showing a value stream of a linear production process modelled using the set of symbols proposed by Rother and Shook. The example depicted here is taken from a simulation environment that allows a dynamic assessment of the values stream using discrete-event simulation in addition to static value stream modelling.

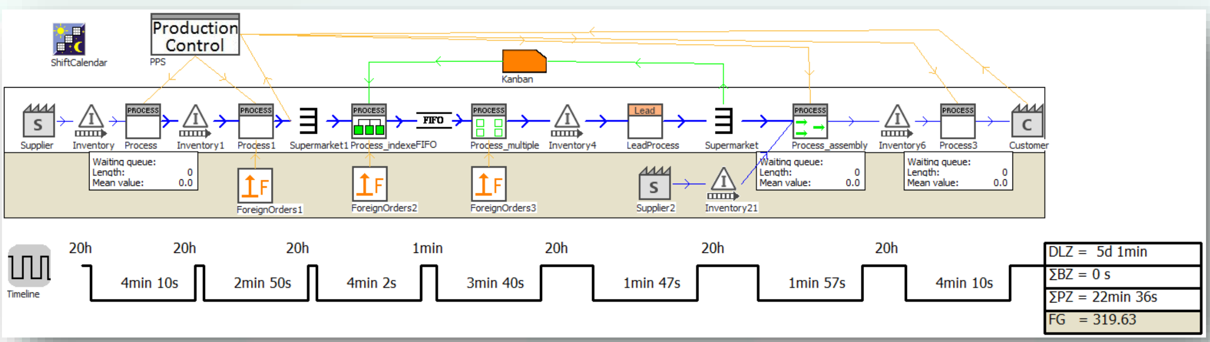

Figure 11. Sample value stream model.

Each value stream object like a process, a buffer, supplier, or customer does have several attributes and data describing its behaviour. Some of the data is process dependent and some depends on the process and the product as the example in Figure 12 is showing.

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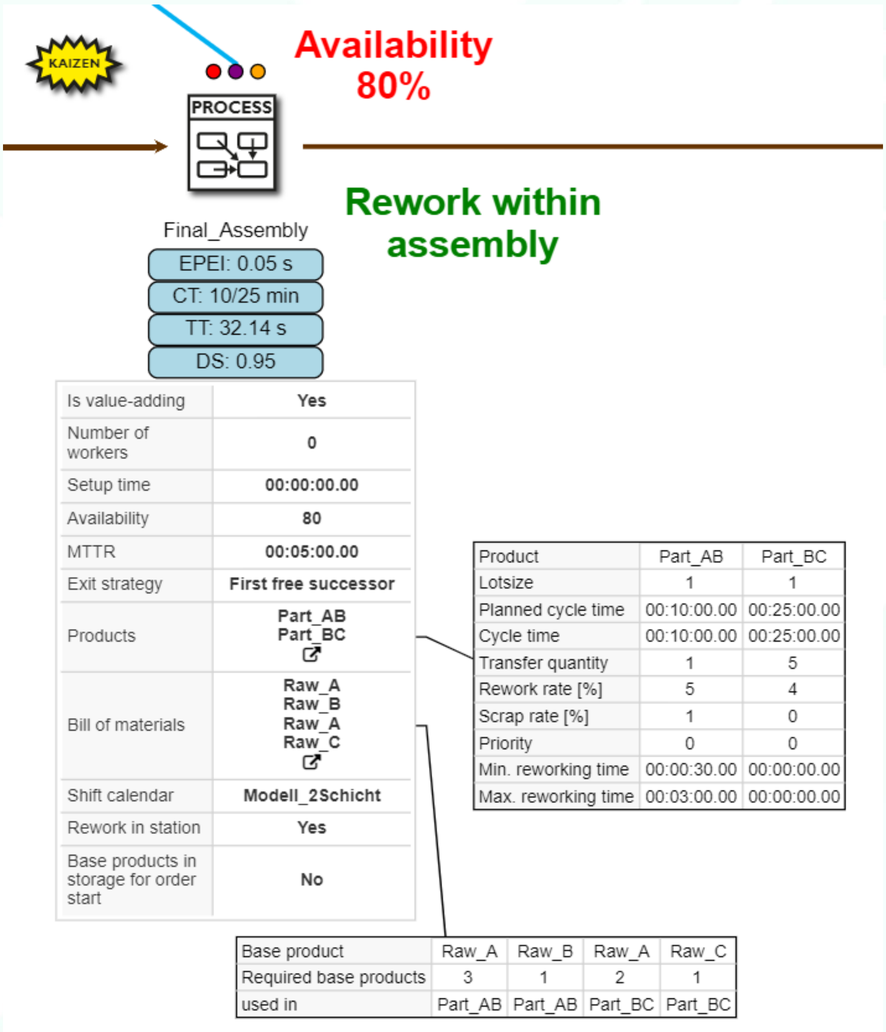

Figure 12. Sample parameters of a value stream process

3.3.2. Energy-related VSM

Todays' value stream modelling and value stream simulation approaches are tackling material handling issues. Use of energy such as electrical power, compressed air, water, steam, or CO_2 is calculated and modelled separately. However, an integrated consideration of energy and material flow a holistic value and energy stream approach allows more comprehensive analysis of interdependencies. Parameters like the one depicted in Figure 13 will be integrated in existing VSM solutions in order to be able to analyse energy-related value streams. A detailed specification of energy-related VSM is going to be part of Deliverable D4.2.

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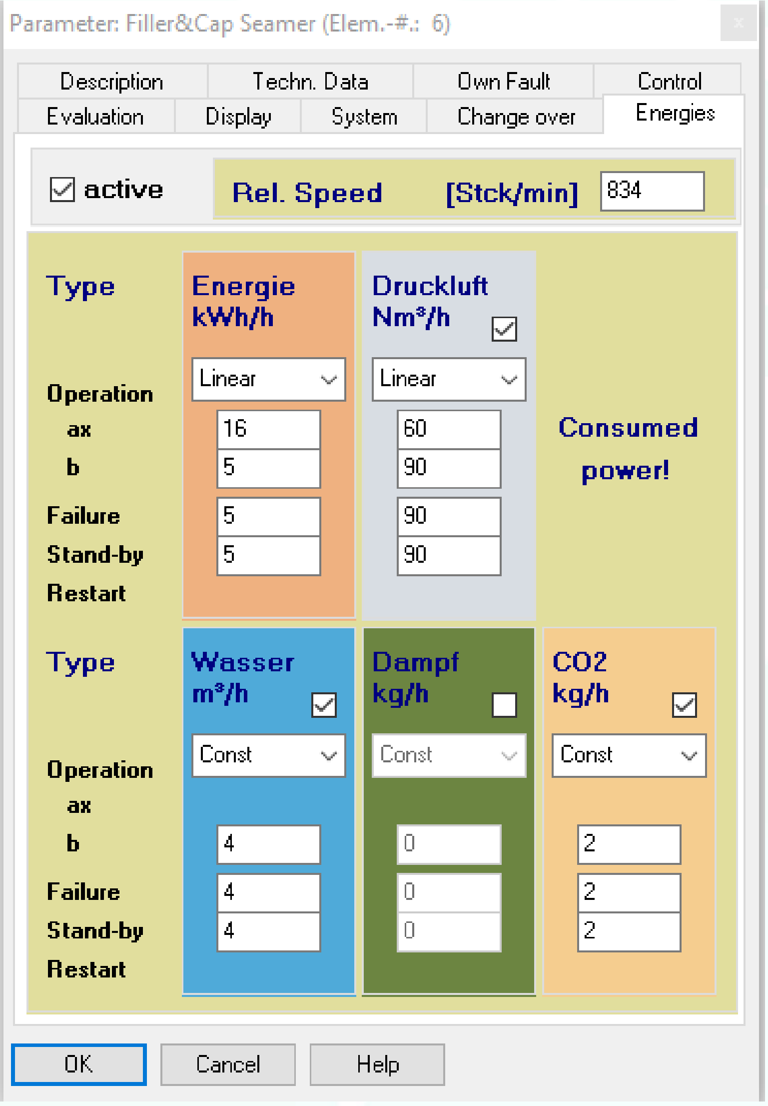

Figure 13. Sample parameters of energy parameters.

3.4. Energy market models /cost models

During the last years the structure of the energy market models has altered significantly due to the unpredictable and uneven production of energy from renewable sources. The massive integration of renewable energy systems into the power network creates the need for modifying appropriately the structure and ways of remuneration within an energy market.

In general, an electricity market consists of various market actors and participants. The actors in this energy market chain are categorized to power producers, retailers, power consumers, market, and system operators. In European countries, the electricity price is determined via a market-clearing procedure, in which each one of the market actors aims to the maximisation of his profit. The clearing mechanism is marginal pricing, in which the marginal producer defines the equilibrium point between supply and demand and thus sets the final price which is applicable to any participant who has a dispatch order from the market. To this end, any producer who sells power within a specific market interval gets remunerated at this price, while at the same time the retailers, who have to procure energy in the day-ahead market (DAM) to cover their customer's energy needs, buy energy at this marginal price. For electricity price forecasting purposes, the main objective is to minimise the difference between the predicted values of the hourly price and the respective day-ahead market values. Minimising this difference, leads to better decisions in the DAM market, decrease of operational costs, better planning of the resources, maintenance schedule etc., [33].

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Additionally, both electricity energy prices and source mix are variables based on the specific time of the day and the period of the year. Synchronising energy-consuming production tasks with "green" energy availability is crucial for sustainable production. To achieve sustainability, variability of energy production should be incorporated in the production scheduling process. Figure 14 presents a typical electricity market production variability.

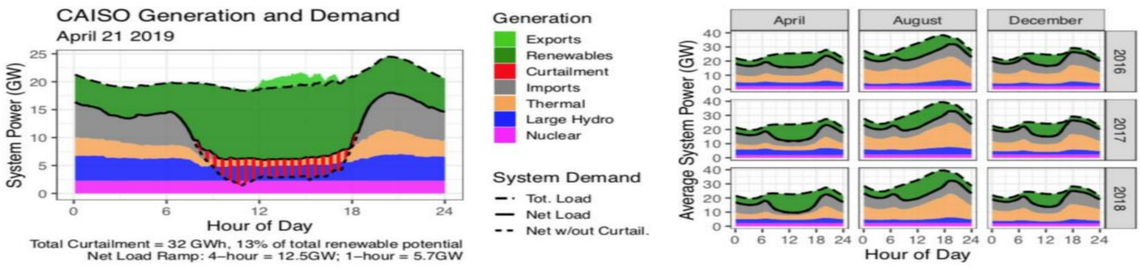

Figure 14. Typical Electricity Production variability.

Forecasting models are divided in three main categories, short, medium, and long term according to the time depth they investigate. In EnerMan, we focus mainly on short-term forecasts for the prices of the DAM market. Those models are based either in statistical or deep learning methods, or in their combination (hybrid methods) [34, 35], creating the respective forecasting engines.

More specifically, models using statistical methods rely on linear regression, which assumes a linear relationship between the independent input variables x (regressors) and the single dependent output variable p (price). The regression model is estimated using ordinary least squares by minimising the residual sum of squares. However, this approach can alter according to the number of the input variables. In our case where many input variables are present, the accuracy of the model is improved with the usage of least absolute shrinkage and selection operator (LASSO) for the estimation. Regarding deep learning methods, the capabilities of the neural networks have been exploited for the DAM price forecasting. There is a variety of deep learning models, which use among others DNN, CNN, RNN, resulting in different forecasts (e.g. a model sensitive to price spiking) [36, 37, 38, 39, 40, 41]. Finally, hybrid methods, [37, 42], combine statistical and deep learning methods, in an effort to eliminate models' individual weaknesses.

Within EnerMan project, electricity price deterministic forecasting tools will be developed for the different pilot countries. The main inputs which will be required by the end user will be (a) selection of the country code and (b) the forecasting horizon (ranging from 1 day ahead to 1 week ahead). The output of the algorithm will be a multi series interval (24 in total), which will indicate the prices of DAM market for each hour of the day. It is evident, that different types of models with different sets of inputs [4] will be employed depending on the forecasting horizon. Specifically, the models that will be employed will be:

- (Benchmark) regression models (e.g., Ridge, Lasso regression).
- Tree based regression models (e.g., Random Forest, XG Boost).
- AI models (e.g., ANN, LSTM).

The input of the implemented models can be sourced publicly from various data sources. Finally in an attempt to exploit the advantages of individual algorithms, hybrid algorithms may arise.

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4. ENERMAN FORMAL MODEL REPRESENTATION

This chapter aims to provide the EnerMan meta-model. In order to do so, the requirements and structure are analysed. The meta model aims to allocate all EnerMan relevant energy flows and leverage the coupling with all kinds of previously collected models.

4.1. Modelling description languages in EnerMan context

As the EnerMan project deals with plants containing a variety of models resulting in complexity, a structured way of representation is sought. A similar challenge can often be found in software engineering. For complex software projects, a model description can be used to reduce the complexity and to define the architecture to build. For the description, modelling languages such as the Unified Modelling Language (UML) can be used. In technical domains other than software engineering, alternatives, specialised on differing requirements, also exist. Commonly used languages in systems engineering are for example the Systems Modelling Language (SysML).

In the EnerMan context, for the considered complex systems, a modelling description language shall also be chosen. However, modelling description languages are generally aimed at the development or planning phase, viz. a green field approach. As the EnerMan project deals with existing production systems, this fact must be taken into consideration for the selection of a modelling language. There are also other criterions to consider which can be grouped into imageability and usability as shown in the following Table 3. The requirements shown originate from the collection of models as well as the initially gathered requirements from the deliverable stated in Table 1. A major criterion among requirements is the reduction of modelling effort through reusability, but also the inherent ability to exchange the created models.

Table 3. Requirements for the formal model representation language in the EnerMan context.

Criterion	Requirement
Imageability	Integration of products, machines and environmental data
	Adaptability to life cycle (machine, production system)
	Modelling accuracy variable
	Multidimensional energy costs (CO_2, financial costs)
	Multiple energy sources can be mapped
Usability	*Simplicity of modelling and nestability*
	Reusability of existing models
	Readable, open file format
	Coupleable (simulation, reality)
	Brown-field compatible

In the given context a variety of description languages and tools were researched and rated afterwards. A preliminary rating revealed, the most suitable modelling languages were UML and SysML. Considering complete modelling tools, Matlab's system composer is an integrative, yet flexible toolbox as alternate modelling description approach, which also received a rating for further consideration.

Each of these proposed modelling methods has its limitation in the given situation. Although Matlab's system composer is a proprietary tool and requires a license, it can be utilized for the modelling of existing systems. SysML features a strongly verification based, four pillar system, which is not necessary in a brown field context. UML is mostly used in the software engineering domain and the class representation is strongly related to the object-oriented programming paradigm. It is however, easier to adapt to a brown field approach than SysML. Another disadvantage of these modelling methods and languages is the missing energy focus. For the EnerMan project, the usage of an adapted version of UML was proposed.

To adapt the UML, a fundamental understanding of meta-modelling description languages is necessary. The definition of UML originates from the Meta object family (MOF). MOF is an Object

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Management Group (OMG) administered meta-meta model and describes the objects characteristics, relations, and formalism. This enables the exchangeability of subordinated model descriptions, [43]. In the UML context, four model levels are featured. These include the MOF, UML, user, and instance models. In order to provide the EnerMan needed extensions to UML an additional meta layer is added. Therefore, the UML specification does not have to be altered. The resulting meta-model hierarchy as well as a comparison is featured below in Table 4.

Table 4. OMG [44] versus EnerMan meta-model hierarchy.

OMG Model level	EnerMan Model level	Modelling description aspect
M3	**M4**	Meta object facility (MOF)
M2	**M3**	Unified Modelling Language (UML)
-	**M2**	EnerMan meta-model
M1	**M1**	User models
M0	**M0**	Instance models

The proposed meta-model hierarchy fulfils the purpose to have three relevant levels to consider and alter for the modelling of the energy flow. The EnerMan meta-model defines the meta classes, which can be utilized by model templates. Model templates shall provide abstract and reusable templates to be used cross-pilot wise. On the M0 level the relevant model templates can be instantiated with their respective parameters. An exemplary procedure for an asynchronous motor is shown afterwards in Figure 15.

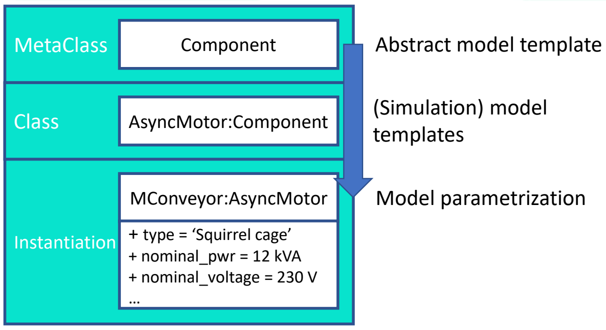

Figure 15. Instantiation workflow from the EnerMan meta-model to parametrized components.

4.2. Meta-model specification

Based on the collection of models and the model taxonomy, some insights, and requirements for the structure of the meta-model were given. A key factor and novelty of the meta-model is the reusability and cross-domain applicability of the used models. The meta layer of the meta-model is therefore closely coupled with the collected models respectively model templates.

To facilitate the cross-pilot usage of models, the similarities between the use cases must be identified. Generally, these are assumed to be found on the component level i.e., basic components as electrical motors or conveyors are used in several pilot cases although the component-aggregating machines may have nothing in common and templating has no notable benefits.

The meta-model itself is split in three views consisting of the product, the workshop, and the resource view. Each view follows a specific purpose. The workshop view is the only view interconnected with the other views. In the workshop, the existent static, non-consumable manufacturing equipment is present. The plant and its representative production areas are mainly used for the tracing and allocation of energy flows. The production areas contain energy consumers in the form of machines and respective aggregates. These entities can contain specific parameters regarding their current status and wear level or provide a data interface. Components however can be underlying to aggregates or standalone. Therefore, fixtures are also classified as components, but can be used in

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combination with different aggregates respectively machines. Hybrid components, e.g., batteries can also be modelled as aggregates or components. The related energy exchanges happen in the resource section.

A special entity within the workshop are sensors. Sensors can be assigned on various levels ranging from the workshop area to an individual component. This context is also necessary for the evaluation of sensor values. Another special feature of sensors is the active usage of the defined workshop hierarchy. In case of a sensor assignment to a machine contained aggregate or component, the sensors data transfer may happen by the machines data interface capabilities.

On the template level, the product view provides the necessary manufacturing information. As products are highly individual, cross-pilot templating is not leveraged in this case. Instead, products and processes are defined as blueprints, which can be overridden or parametrized when being instantiated as manufacturing job. In this definition a process occupies a machine and can therefore be used to indicate machine occupancy. Processes itself consist of individual operations, which can utilize different sets of equipment. An example therefore would be milling as process. The milling process happens on a defined milling machine. It however can consist of a roughing and a smoothing operation which need different milling tools at minimum. Also, different fixtures could be included within the equipment set. The operations respectively step also include all relevant manufacturing information to control the specified equipment set.

The product and workshop view are not specifically energy focused. To determine the energy relevant flows a resources view is also included in the EnerMan meta-model. The resource view only interfaces with the workshop area and is therefore independent from the products' manufacturing information's. In fact, the resource view is only coupled with the components as all energy flow is assumed to happen on the component level. With this approach, components can provide multiple resource conversions. Resource conversions as such, are also meant to be templated and to be coupled with behavioural models. Resources itself can represent not only energy but also other manufacturing consumables which allow the allocation of CO_2 equivalent emissions through resource wear.

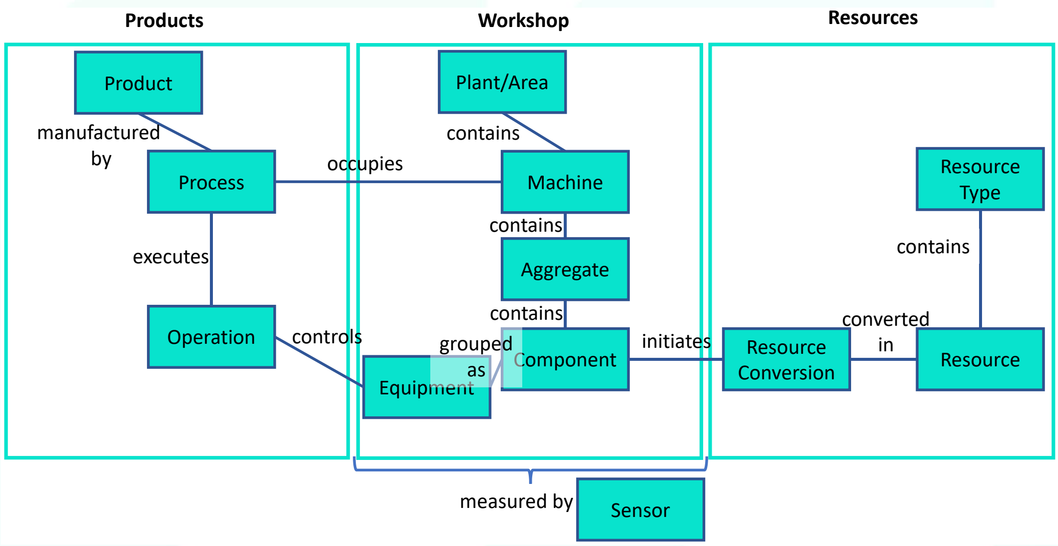

Figure 16. Simplified view of the EnerMan meta-model.

Considering the resulting meta-model, two versions with different grade of detail were created. Figure 16 visualizes the simplified base version. Based on the simplified view, an extended view also exists, which refines the base model by additional details, such as condition awareness, positions, different energy sources and multidimensional cost models.

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4.3. Strategies for energy flow modelling

In order to obtain a reproducible statement about the energy consumed in the manufacture of a product, a corresponding indicator must be used. In economic theory, Costanza's model of inherent product energy [45] is used for this purpose. Here, the consumed energy in manufacturing is allocated to corresponding products.

It should be noted that there are also continuations of this approach which depict further parts or the entire product life cycle. Examples of this are the term "grey energy" and the cumulative energy expenditure calculation [46]. Within the EnerMan project, however, only the manufacturing phase is considered, and these methods are therefore too far-reaching.

One difficulty in mapping the inherent product energy of manufacturing is the structure of the production system. As mentioned in chapter 2, there is a difference between hierarchical structure and energetic supply network. There can also be a difference between the location of energy consumption and the position of the product. This is the case, for example, in supporting processes and energy conversion, e.g., in the production of compressed air electrical energy is consumed, which has to be allocated to the product.

However, there is an existing methodology which can map these characteristics. For this purpose, a methodology is developed based on financial cost accounting, which forms an energetic analogy to direct and overhead cost accounting [47]. Although this methodology originally only aims at the allocation of consumed energy, it can be used to calculate energy costs with the aid of temporal market cost models and the additional information of the timespan, the energy was consumed in.

To allocate the consumed energy pathways can be identified in the meta-model. The direct energy consumption is directly caused by a product associated process, respectively operation. Thus, indirect consumed energy is caused by non-associated processes. These include assisting manufacturing processes for the provision of common resources e.g., compressed air, as well as non-allocable losses. Direct allocation always happens on the lowest hierarchical level. Indirect resource consumption is escalated to the next hierarchy level allocated to products and processes as overhead costs per hierarchical level. As shown in Figure 17 below an energy value stream can be derived.

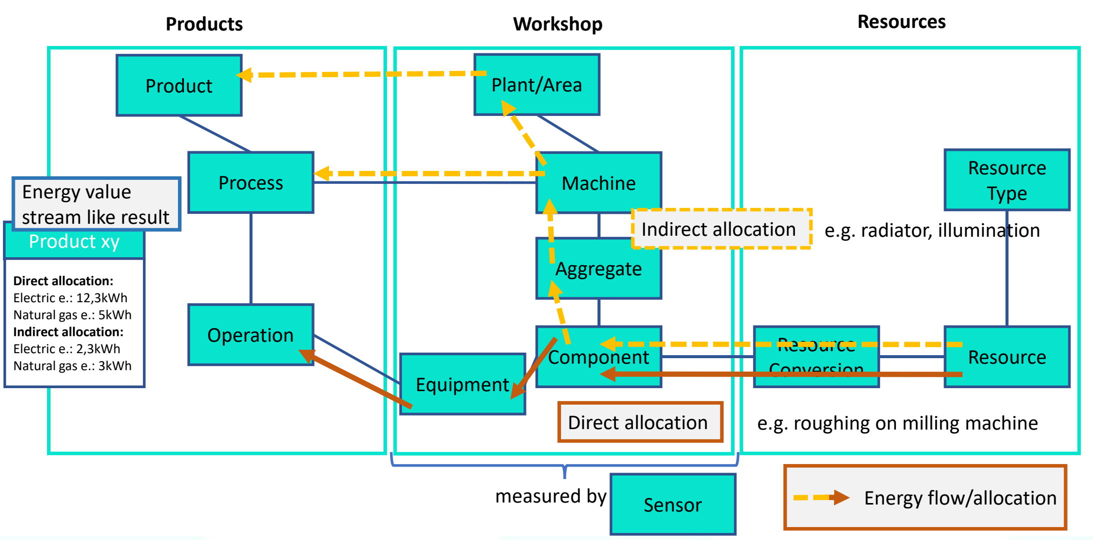

Figure 17. Energy consumption allocation in products in the EnerMan meta-model.

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5. ENERMAN MODELS IMPLEMENTATION

5.1 Application of energy-related flow determination

This section aims to explain the usage of the meta-model in the context of an EnerMan pilot use case. Thus, on a per-subsection basis, the general requirement and approach are explained in general and then selected applications of the CRF use case [48] as also highlighted in D1.2 are presented. The structure of this section includes the extraction of requirements and scope from the available use case data, the creation of formal model templates and concludes with the instantiation of the model layer. An overview of this procedure is visualized in Figure 18. Furthermore, the integration of models within the meta-with models is explained briefly.

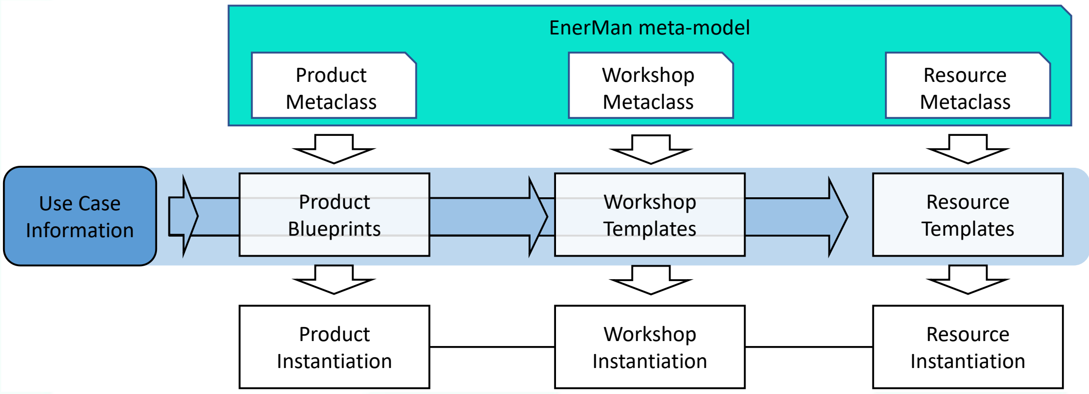

Figure 18. Procedure of the EnerMan meta-model application.

5.1.1. Initial situation and requirements in the use cases

To formally describe a production system with the proposed EnerMan meta-model, several aspects of the targeted system must be known to define the products, shopfloor, and resource view [49]. Practical applications of formal modelling often deal with missing or irrelevant data. Thus, partial modelling can be used to solve this problem. In a first step, the scope of modelling must be defined to set the partial borders. The extraction of information from the production environment is based on the scope set. Necessary information includes

Products and processes

- type of processes (discrete/continuous)
- necessary manufacturing operations and operation order of manufactured products
- manufacturing information and process parameters

Workshop

- shopfloor hierarchy
- relevant machines and their classification
- location information for machines, areas and plants
- relevant sensors and their classification
- available data interfaces

Resources

- scoped manufacturing resources and energy types
- resource type (discrete/float)
- resource sourcing possibilities
- resource cost and availability
- energy consumption/conversion profiles

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Given the CRF use case and practical application, the needed information can be derived from several description documents. The workshop hierarchy and related data can be extracted from a floor plan. The available sensors and data interfaces can be extracted from a station description. The manufacturing goods are represented by car chassis in the body shop and an order of manufacturing processes is given by the chassis manufacturing job description. The boundaries for the partial modelling are set by the use case description and are restricted to the body shop.

5.1.2. Creation of formal model templates

The creation of model templates is an essential part for the inclusion of reusable parametric simulation components. Model templates are the interface between instantiated, respectively physical components and meta-class models. Furthermore, model templates can also serve as simulation modelling templates, i.e., can be used for the creation of parametric, reusable simulation models. A differentiation must be made between model templating and blueprinting. While templating aims to provide reusable models, blueprinting refers to the generic description of manufactured goods or services. Thus, templating is applied for resource and workshop view, while blueprinting is used on the same layer for products.

For the creation of model templates an EnerMan model database could be created for recurring models. To create the templates from scratch, the extracted use case information as well as meta-model types are needed. The templates can be derived by grouping similar entities, e.g., asynchronous motors and assignment to a meta-class, e.g., component. The application of formal modelling in this context is restricted to information modelling and reflects only the attributes, not the behaviour. The behaviour is represented by coupled simulations, which could also be represented by multiple different behavioural modelling techniques. From the derived information of the CRF use case's available sensors, the template classes visualized in Figure 19 could be obtained.

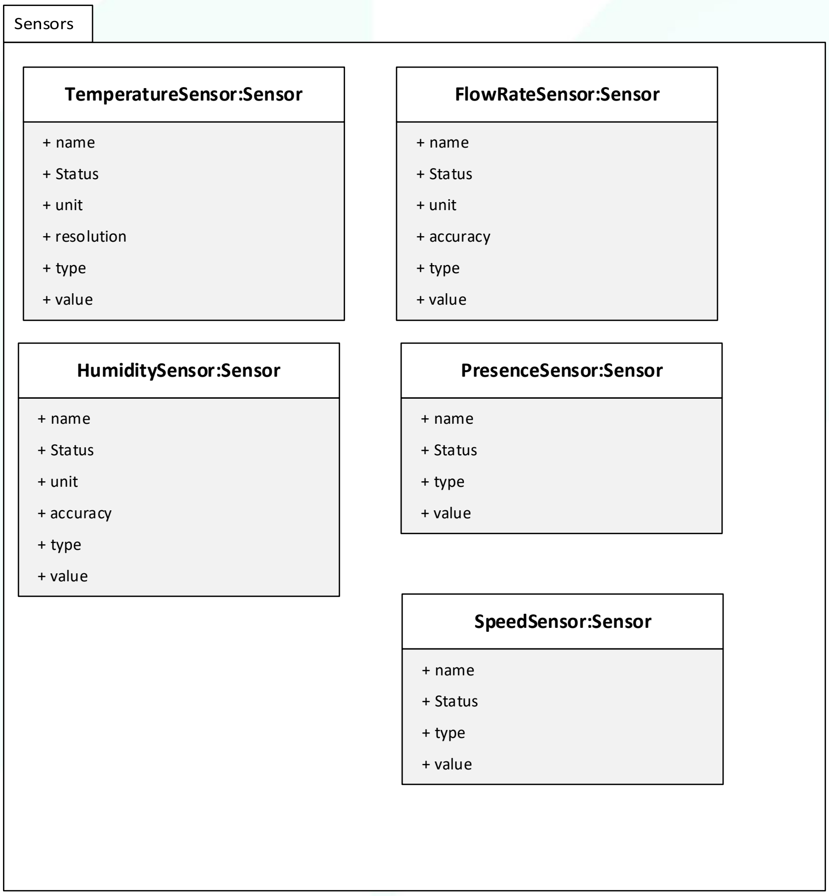

Figure 19. Creation of sensor templates from extracted use case information.

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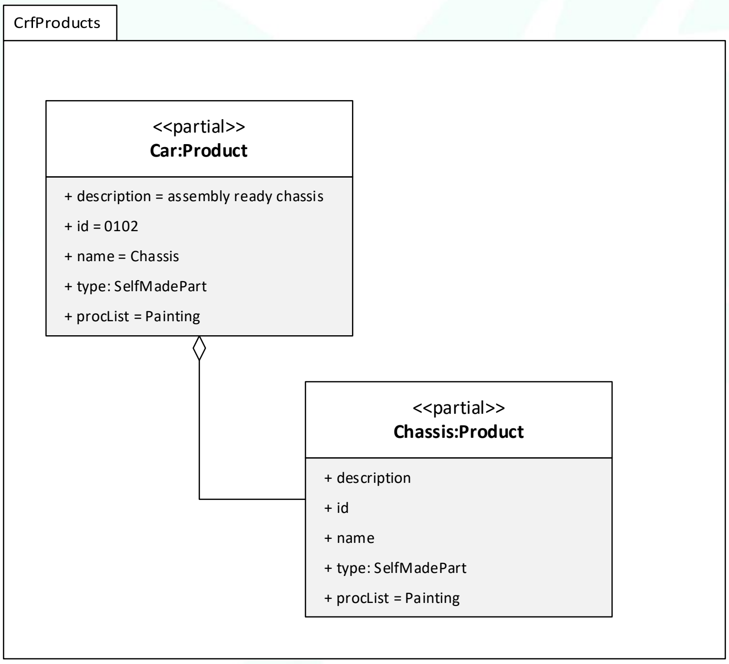

Figure 20. Blueprinting of CRF products.

The product blueprints include the available manufacturing data which can be applied for generic configurations. An example would be the process of painting a car. Though the chassis colour can be adapted, the process itself is not tied to a specific colour. To comply with the set boundaries, the meta-model stereotype “partial” can be used to express only a subset of chassis attributes are modelled but also extensibility is provided as highlighted in Figure 20.

5.1.3. Model layer instantiation

To use the templates and blueprints, instantiation and interconnection are needed. The main problem in this step is the complexity. By modelling real manufacturing environments, a lot of elements occur. To reduce clutter and provide maintainability of formal models, a proper segmentation of diagrams is needed. An example for diagram segmentation can be found in Figure 21. The figure visualizes the hierarchical structure of the workshop with individual positions. As only some aspects of the plant, respectively scoped workshop is modelled, the plant and areas feature the partial stereotype.

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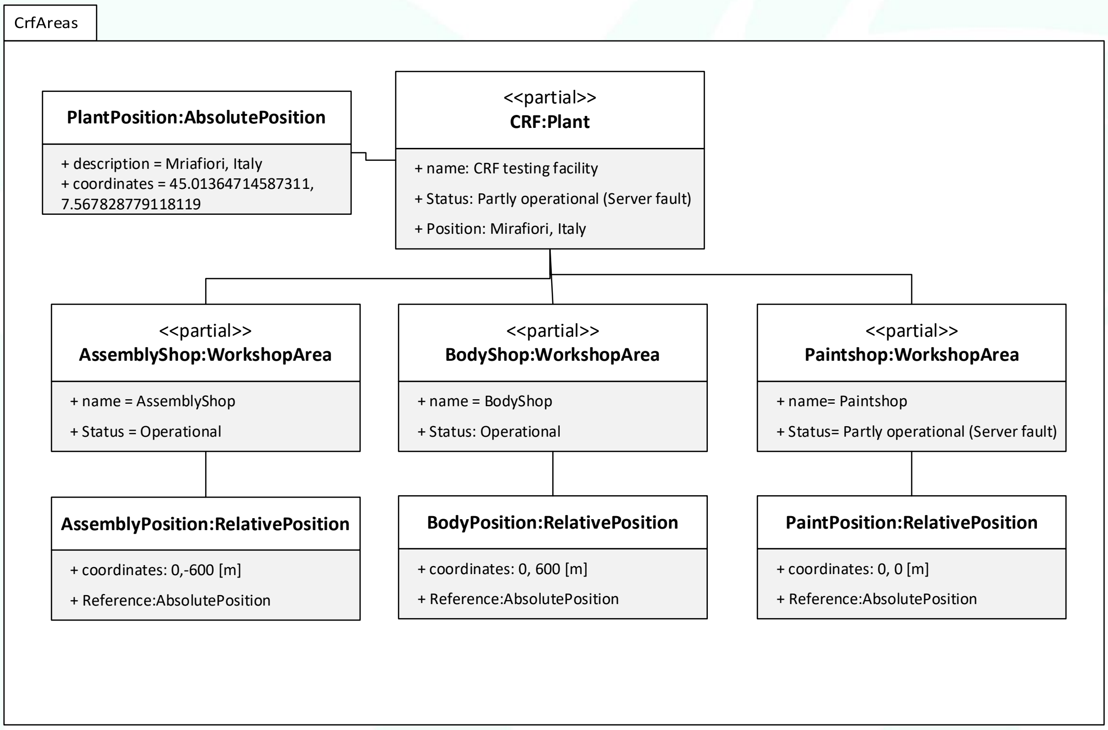

Figure 21. Instantiation of the hierarchical workshop structure.

For the instantiation of other entities, the procedure is similar. As a rule, interconnections are only provided from detailed formal models to abstract formal models. An example within the CRF context is shown below in Figure 22. The instantiation of models thus can be used to obtain current sensor values, if coupled with a data interface. Further usage of the instantiated model includes the derivation of context, e.g., associated zone for sensor values.

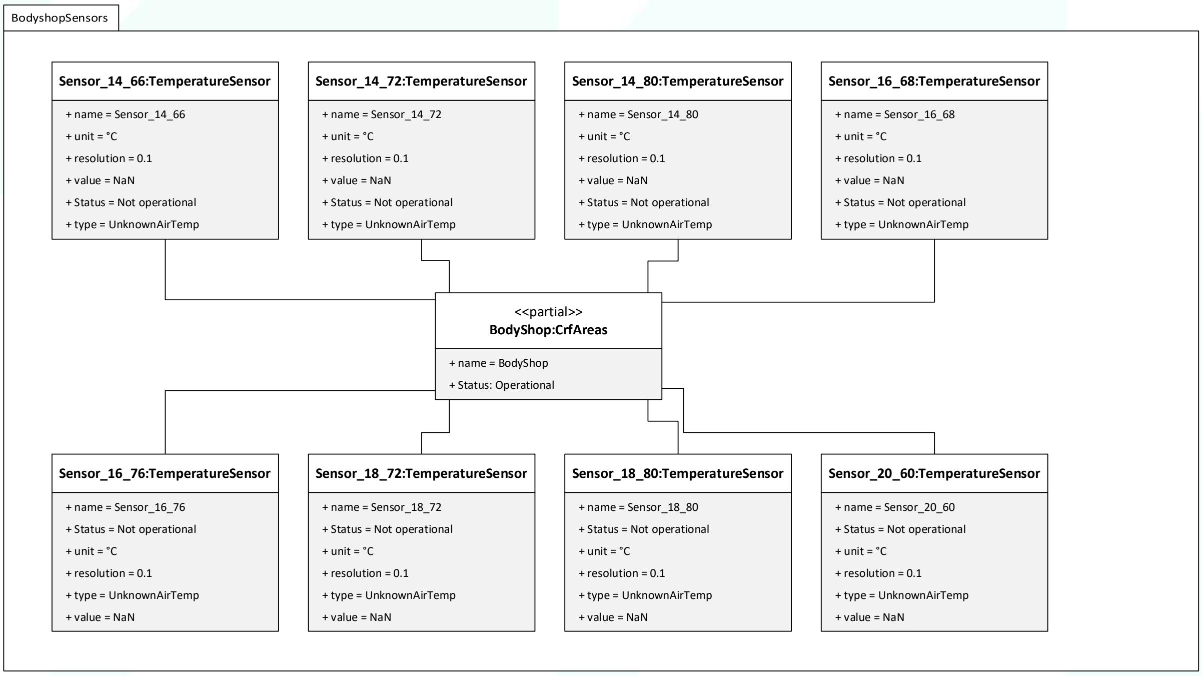

Figure 22. Instantiated sensors for the CRF use case.

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Data sources for the updates of instantiated values can also be provided by behavioural models. A difficulty, not scoped by the EnerMan meta-model instantiation is the coupling of simulations. As obtained by the collection of models, a variety of different simulation techniques are used in the context of a manufacturing system as visualized in Figure 23. These techniques are often fundamentally different, i.e., they are based on different methods to take time into account. Discrete event simulation for example only considers short events, which feature a varying timespan between. Analytical models may be solved for continuous time periods, while numerical simulation methods feature a fixed or dynamic time step of an underlying ODE solver [50]. Thus, the integration of behavioural models can be carried out in two different ways.
The first possibility is the integration per simulation technique, i.e., numerical simulations may be integrated on the same level. For the intra-level coupling of simulations, existing approaches can be used. For example, analytical models can be coupled by joining equations or simultaneous solving of mathematical problems. Numerical simulations may be integrated by using existing standards like Functional Mockup Interface (FMI)[6]. FMI already supports a wide range of common simulation tools, e.g., Matlab/Simulink®, Ansys®, NI LabView®, but also the integration of custom solutions built with common programming languages, e.g., Python, Java, C++.
The integration between different simulation techniques is not directly possible. However, as the integration of continuous updates is crucial to maintain reliability of simulations and optimization, an indirect possibility is needed. The indirect integration of models is covered by application programming interfaces (API). To realize the data exchange between simulations, a communication between the individual simulations is needed. The specification of data interfaces and related intermediate technologies for decoupling time aspects, e.g., databases, is however, covered by the creation of the simulation engine and the contents of work package 5. The meta-model applications and simulation coupling possibilities provide a basis for the overall architecture and cross work package integration.

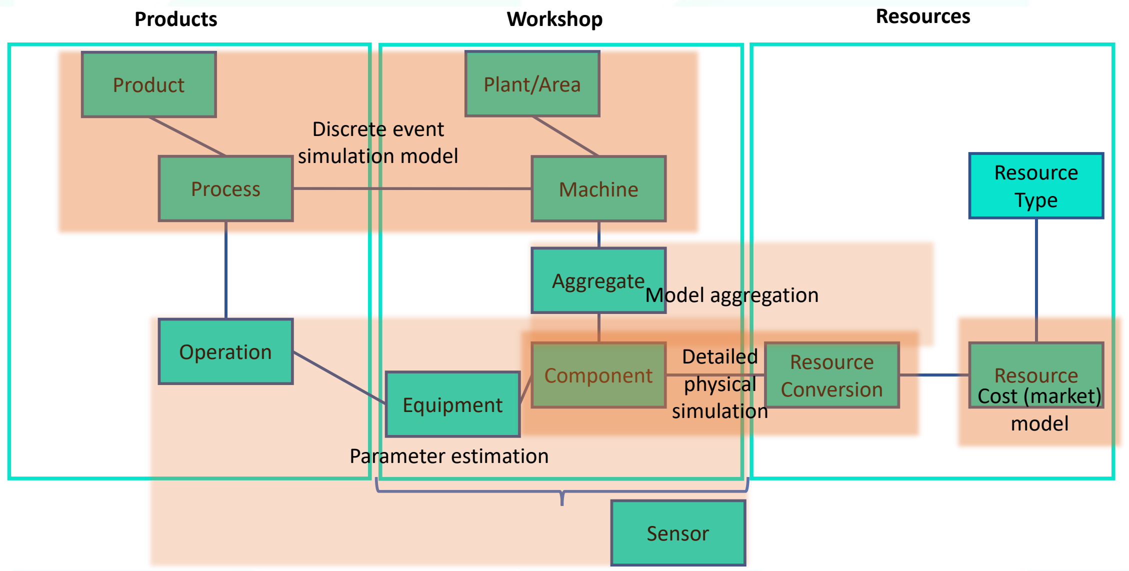

Figure 23. Visualization of occurring simulation techniques and mapping to the EnerMan meta-model.

5.2. CRF bodyshop prediction engine: thermodynamic model

The following chapter deals with the implementation and training procedure of the EnerMan prediction engine. The proposed method is based on the development of a digital twin of the real physical system under consideration. This twin is designed through analytical state models, which

[6] https://fmi-standard.org/

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usually present a series of unknown or poorly known parameters. During the learning phase, the models are connected to the sensors in real time thanks to the integration of Kalman filters. This approach allows to gain insight into the unknown properties of the system and manage uncertainties due to modelling approximations and noisy sensor data. Once the parameters are identified, the state models are employed to provide a forecast of energy consumption.

The methodology is detailed with reference to the CRF bodyshop, which is one of the EnerMan use-cases in the automotive manufacturing sector. The target process of the use-case concerns the environmental heating and the air conditioning of the industrial building, which account for a major part of total energy demand of the car production plant. The indoor air temperature of the working area must be kept around 18°C to ensure the well-being and health of the personnel.

In this context, the digital twin takes a dual purpose: firstly, the prediction of the indoor temperature trend and the heating load in scenarios with external weather conditions assumed a priori; secondly, the acquisition of information on the thermal characteristics of the building and on the thermal contributions that are not directly measurable. The heating load is the quantity of thermal energy per unit time that must be supplied to maintain the temperature in a building, or portion, at a given level. Monitoring and scheduling optimization of HVAC systems offer significant potential to improve energy efficiency and sustainability in industrial buildings.

5.2.1. Use-case description and available data

The bodyshop of FCA's plant in Mirafiori (Turin) is an example of flow shop or transfer line, where many parts are assembled together by welding operations. It is a huge industrial warehouse (Figure 24) that covers about 120000 m^2. The whole area is divided according to the type of operation carried out along the assembly process and the vehicle model, but often there are no real dividing walls between the various working areas.

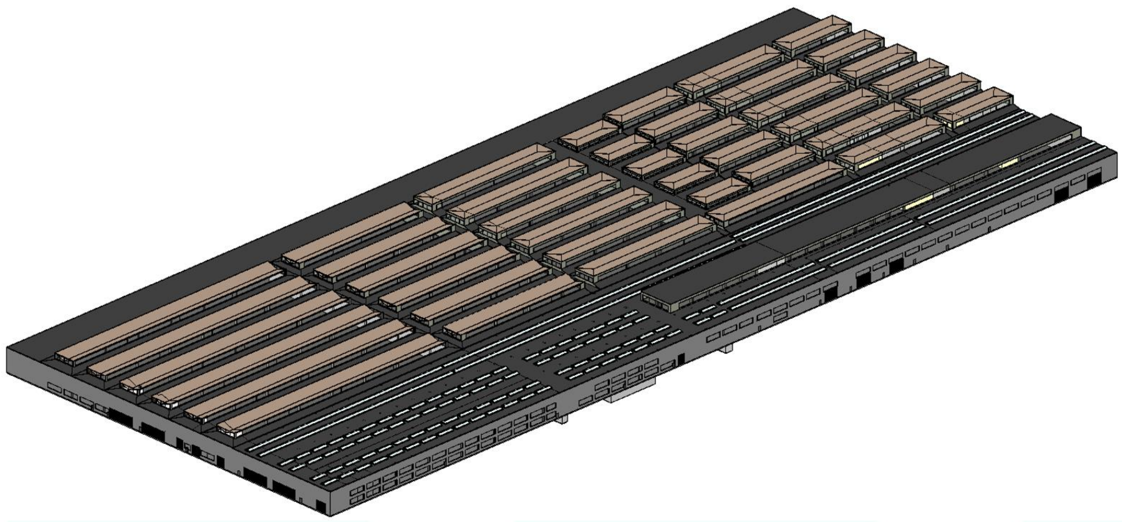

Figure 24. Bodyshop 3D model (Autodesk Revit).

The data made available by CRF are listed in Table 5.

Table 5. Available data provided by CRF.

Data	***Sampling rate***	***Overall sampling period***
Indoor temperature	15 min	29/01/2019 - 13/09/2019
External weather conditions	Hourly	15/04/2018 - 14/04/2019
Scheduling HVAC systems	Daily	15/10/2017 - 15/04/2018 15/10/2018 - 30/04/2019
Energy consumption for heating	Monthly	10/2017 - 04/2019

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External weather conditions include outdoor dry-bulb temperature T_{out}, outdoor dew-point temperature, direct (beam) normal irradiance E_b, diffuse horizontal irradiance E_d, wind speed and direction, atmospheric pressure, solar altitude β and solar azimuth ϕ. The indoor air temperature is measured through a wide sensor network distributed throughout the plant. Two different acquisition systems are adopted: the first is wired to PLCs, the second uses wireless IoT meters. The position and installation height of the sensors are known. The bodyshop 3D model (Autodesk Revit) provides the location and size of glazing surfaces, doors and gates and the building orientation, then the azimuth angles of the external surfaces.
Heating and air conditioning are carried out by three types of AHUs and unit heaters. The AHUs are provided with air supply ducts and manually adjustable dampers for internal exhaust air. There are unit heaters for both internal air recirculation and outdoor air supply. The heating of the supply air flow to be introduced into the bodyshop is obtained by heat exchange with a superheated water flow. Type 1 AHUs and unit heaters have no automatic regulation: switching on/off of fans is managed manually (on the electric panels in the workshop) according to the daily schedules. Type 2 and type 3 AHUs are equipped with temperature probes for regulation and fixed air flow rate fans, which are switched on according to the daily scheduling and switched off when the desired set-point is reached. The regulation is carried out by opening/closing the superheated water supply valve. The switching on/off of the fans and the regulation of the valves is managed by a central server through two PLCs.
CRF also shares the results of a previous research work performed by researchers of the Politecnico di Torino on simulated data. In their study, authors predicted the temperature profiles in the buildings through grey-box models based on Kalman filters, [51, 52].

5.2.2. RC model for thermal dynamics in non-residential buildings

Many simulation models have been developed to describe thermal dynamics in buildings, [53]. Following the lumped parameter approach, the entire building is represented by means of a few thermal elements, namely thermal resistors, and capacitors, [54, 55, 56, 57]. These elements do not necessarily embody single physical elements, but they can be equivalent to multiple thermal elements and physical effects. The model is built as an RC circuit by using the electrical network analogy: the temperature is the voltage, and the heat flux is the current. The building is divided into thermal zones, which correspond the nodes of the circuit. Each resistor represents the equivalent thermal resistance of the elements placed between two zones, such as walls, windows, roofs, floors, and air. Each capacitor connected to a node expresses the thermal capacity of the air mass of the zone. The connecting nodes are associated with the temperature of the zones. The building can be modelled by a single-zone or multi-zone circuit depending on the level of detail (Figure 25): in a single-zone model the unique heat exchange is with the external environment; a multi-zone model also considers the heat exchange between adjacent zones. The order of the model is equal to the number of the nodes (capacitors). The governing equations are derived from the thermodynamic and heat transfer laws.

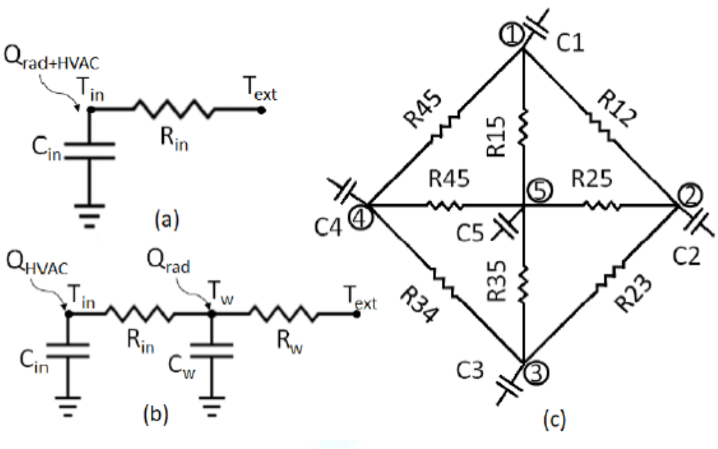

Figure 25. Thermal networks representation: a) single-zone 1-node, b) single zone 2-node, c) multi-zone 1-node; from [51].

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The variation of temperature for the i-th node is given by the energy rate balance (kinetic and potential energy effects are neglected):

$$C_i \frac{dT_i}{dt} = \sum_j \frac{T_j - T_i}{R_{ij}} + \sum_k \Phi_{k,i} \tag{9}$$

where C_i [J/°C] is the thermal capacity of the i-th zone, T_i [°C] is the temperature of the i-th zone, T_j [°C] is the temperature of the j-th adjacent zone or the outdoor temperature, R_{ij} [C°/W] is the equivalent thermal resistance between the i-th zone and the j-th zone, $\Phi_{k,i}$ [W] is the k-th heat gain (loss if negative) of the i-th zone.
The first term of the right-hand side expresses the heat transfer between nodes, i.e., heat flows driven by temperature differences. The equivalent resistance R_{ij} combines different physical effects: conduction, convection, and radiation. This is a quite accurate representation for conduction and convection, while it is just a linear approximation for radiation, [58]. Heat gains $\Phi_{i,k}$ represent both sensible heat flows and latent heat flows due to internal and external heat sources. Sensible heat contributions are added directly to the conditioned space by heat transfer processes and result from HVAC systems, solar radiation on transparent and opaque external surfaces, infiltration of outdoor air, occupants, lights, machines, electrical appliances and heat loss by infrared radiation to the sky. Latent heat gain or loss occurs when moisture is introduced or removed from the space, and result from water vapor emitted by occupants and equipment, from humidification or dehumidification systems and moist air streams.
The heat gains on which the data are available are modelled, otherwise they are considered as disturbances and collected in a single term $\Phi_{dist,i}$. In this first analysis, the sensible heat gains due to HVAC systems $\Phi_{HVAC,i}$ and solar radiation $\Phi_{solar,i}$ are investigated. All other mentioned thermal contributions are included in $\Phi_{dist,i}$, as well as the heat transfer through the floor.
The heat input of HVAC systems is expressed as (see [17]):

$$\Phi_{HVAC,i} = \dot{m}_{HVAC} c_{pa} (T_{HVAC} - T_i) \tag{10}$$

where $\dot{m}_{HVAC}$ is the mass flow rate [kg/s] of supplied air, c_{pa} [J/(KgK)] is a constant value for the specific heat of dry air, T_{HVAC} is the air flow temperature at the HVAC system outlet and T_i is the temperature of the i-th zone. If $\dot{m}_{HVAC}$ and T_{HVAC} are not known a priori, they can be calculated by applying the mass and energy balance to the HVAC system including the heat exchange with the superheated water flow. The term $\Phi_{HVAC,i}$ is introduced in the model according to the scheduling of the HVAC systems and the heating regulation-actuation procedure.
The solar heat gain through fenestration's glazing surfaces is formulated by assuming the isotropic sky model (see [59]- [60]) to calculate the solar radiation on tilted surfaces:

$$\Phi_{solar} = A\left[E_{b,t} SHGC(\theta) + (E_{d,t} + E_{r,t}) SHGC_{avg}\right] \tag{11}$$

where $E_{b,t}$ [W/m^2], $E_{d,t}$ [W/m^2] and $E_{r,t}$ [W/m^2] are the beam, diffuse and ground-reflected irradiance, respectively, on the tilted surface, A_i [m^2] is the window area, $SHGC(\theta)$ and $SHGC_{avg}$ are the solar heat gain coefficients as a function of the incidence angle θ and as a hemispherical average value, respectively (please refer to [61] for the definition of the $SHGC$). The previous expression applies to each set of glazing surfaces having the same tilt angle and azimuth angle and simplifies for horizontal and vertical windows, as in the case of the bodyshop.
By introducing $\Phi_{HVAC,i}$, $\Phi_{solar,i}$ and $\Phi_{dist,i}$, the energy rate balance of the of the i-th zone becomes:

$$C_i \frac{dT_i}{dt} = \sum_j \frac{T_j - T_i}{R_{ij}} + \Phi_{HVAC,i} + \Phi_{solar,i} + \Phi_{dist,i} \tag{12}$$

As an example, it is possible to consider a building consisting of two adjacent thermal zones. The equivalent RC model includes two state equations describing the evolution of the indoor air temperature T_i:

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$$C_1 \frac{dT_1}{dt} = \frac{T_2 - T_1}{R_{12}} + \frac{T_{out} - T_1}{R_{1,ext}} + \Phi_{HVAC,1} + \Phi_{solar,1} + \Phi_{dist,1} \quad (13)$$

$$C_2 \frac{dT_2}{dt} = \frac{T_1 - T_2}{R_{12}} + \frac{T_{out} - T_2}{R_{2,ext}} + \Phi_{HVAC,2} + \Phi_{solar,2} + \Phi_{dist,2} \quad (14)$$

where subscripts 1 and 2 refer to zone 1 and zone 2, respectively, T_{out} is the outdoor temperature, $R_{1,ext}$ is the equivalent thermal resistance between zone 1 and the external environment and $R_{2,ext}$ has the same meaning for zone 2. The physical system is represented by a set of continuous ordinary differential equations. The number of equations equals the number of thermal zones.

The zoning of the bodyshop area is performed by taking into account the arrangement of the three types of AHUs and their regulation-actuation mode: it is convenient that each thermal zone contains either AHUs controlled manually or by PLCs, in this way any modification to the heating scheduling can be applied more easily. The use of techniques such as singular value decomposition which can reduce the dimensionality of problems (see [62]) can help in the subdivision, identifying sensors that present temperature trends with common characteristics.

5.2.3. Extended Kalman Filter (EKF)

Kalman filtering [63] is a common data fusion algorithm, which uses the system's state model and multiple sequential measurements acquired by sensors to find an estimate of the system's states. Kalman estimators deal successfully with the uncertainties due to noisy sensor data and the virtual model, which is usually characterized by several approximations. The EKF is a prediction-correction algorithm. In the prediction step, the filter produces an estimation of the current state variables, along with their uncertainties. Once the next measurement is observed, these estimations are updated by computing a weighted average.

The process of interest is represented through the model discretized in the time domain. The general expressions of the state equation and the observation equation are:

$$\boldsymbol{z}_k = \boldsymbol{f}(\boldsymbol{z}_{k-1}, \boldsymbol{u}_k) + \boldsymbol{w}_k \quad (15)$$

$$\boldsymbol{y}_k = \boldsymbol{g}(\boldsymbol{z}_k) + \boldsymbol{v}_k \quad (16)$$

where k is the time index, $\boldsymbol{z}$ is the state vector, $\boldsymbol{u}$ is the input vector, $\boldsymbol{w}$ is the process noise vector, $\boldsymbol{y}$ is the measurement vector, $\boldsymbol{v}$ is the measurement noise vector, $\boldsymbol{f}$ is the non-linear state transition function, which is applied to the previous states to generate the next states, and $\boldsymbol{g}$ is the non-linear observation function, which is applied to the states to generate the observed outputs. Process noise $\boldsymbol{w}$ and measurement noise $\boldsymbol{v}$ are assumed to be multivariate Gaussian distributions with zero mean and covariances $\boldsymbol{Q}$ and $\boldsymbol{R}$, respectively. The EKF applies to non-linear systems: the non-linear functions $\boldsymbol{f}$ and $\boldsymbol{g}$ are linearized around the mean of the current state estimate by using a first-order Taylor series expansion. At each time step, the linearization is performed locally and the resulting Jacobian matrices $\boldsymbol{F}$ and $\boldsymbol{G}$ are used in the prediction and in the correction steps ($\boldsymbol{f}$ and $\boldsymbol{g}$ must be continuous and differentiable functions).

The EKF algorithm is formulated as follows. The prediction step is:

$$\hat{\boldsymbol{z}}_{k|k-1} = \boldsymbol{f}\left(\hat{\boldsymbol{z}}_{k-1|k-1}, \boldsymbol{u}_k\right) \quad (17)$$

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{F}_k \boldsymbol{P}_{k-1|k-1} \boldsymbol{F}_k^T + \boldsymbol{Q}_k \quad (18)$$

The state estimate from the previous time step $\hat{\boldsymbol{z}}_{k-1|k-1}$ and its covariance $\boldsymbol{P}_{k-1|k-1}$ are used to produce the predicted state estimate at the current time step $\hat{\boldsymbol{z}}_{k|k-1}$ and its covariance $\boldsymbol{P}_{k|k-1}$. The estimate covariance $\boldsymbol{P}$ provides a measure of the uncertainty in the state estimate. The correction step is:

$$\boldsymbol{K}_k = \boldsymbol{P}_{k|k-1} \boldsymbol{G}_k^T \left(\boldsymbol{G}_k \boldsymbol{P}_{k|k-1} \boldsymbol{G}_k^T + \boldsymbol{R}_k\right)^{-1} \quad (19)$$

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$$\hat{\boldsymbol{z}}_{k|k} = \hat{\boldsymbol{z}}_{k|k-1} + \boldsymbol{K}_k \left(\boldsymbol{y}_k - \boldsymbol{g}(\hat{\boldsymbol{z}}_{k|k-1}) \right) \tag{20}$$

$$\boldsymbol{P}_{k|k} = (\boldsymbol{I} - \boldsymbol{K}_k \boldsymbol{G}_k) \boldsymbol{P}_{k|k-1} \tag{21}$$

where $\boldsymbol{K}$ is the Kalman gain matrix and $\boldsymbol{I}$ is the identity matrix. The current prediction $\hat{\boldsymbol{z}}_{k|k-1}$ is combined with current measurement $\boldsymbol{y}_k$ to improve the state estimate and its covariance. The Kalman gain $\boldsymbol{K}$ determines how heavily $\boldsymbol{y}_k$ and $\hat{\boldsymbol{z}}_{k|k-1}$ contribute to the computation of the updated state estimate $\hat{\boldsymbol{z}}_{k|k}$.

Only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. No history of observations and estimates is required, then the algorithm can run in real time. If an observation is unavailable for some reason, the correction may be skipped, and multiple prediction steps performed. In order to initialize the algorithm, it is necessary to start with an initial guess of the state $\hat{\boldsymbol{z}}_{0|0}$ and an initial estimate covariance $\boldsymbol{P}_{0|0}$. If there are few uncertainties in $\hat{\boldsymbol{z}}_{0|0}$ then $\boldsymbol{P}_{0|0}$ is small and vice versa. Contrary to the standard Kalman filter, if the system is highly non-linear or the initial guess is wrong, the EKF may diverge. It is necessary to perform numerical tests to control the behaviour of the algorithm and validate the procedure.

5.2.4. Implementation procedure: training and prediction

In the learning phase, the equivalent RC model describing the thermodynamics of the bodyshop is connected with the EKF in order to get several information in return. The EKF task is to train the model with a series of sensor measurements. By introducing the unknown parameters, namely capacitances C_i and resistances R_{ij}, and disturbances $\Phi_{dist,i}$ in the state vector $\boldsymbol{z}$, they are identified as the EKF algorithm proceeds in the estimation of all the state variables.

If there are many thermal zones, it is more difficult to model all the uncertain phenomena and the filter becomes no longer able to divide the contribution coming from one zone rather than another: the higher the number of thermal zones, the greater the number of unknowns that the EKF needs to estimate. This increase in the size of the filter's state space could limit its performance leading to divergence issues. To overcome the problem the whole set of zones is not considered in the same state space. Instead of implementing a single filter for managing all the thermal zones, it is possible to use a bank of EKFs that run in parallel. Each filter works on a single thermal zone and the contribution of the nearby areas is considered as an input. Having a dedicated filter for each thermal zone, i.e., a multi-filter algorithm, enhances the accuracy of the results, as shown in [52]. This method reduces drastically the number of variables that a single EKF has to manage.

The augmented state vector $\boldsymbol{z}_i$ of each filter includes indoor air temperature, unknown parameters, and disturbances:

$$\boldsymbol{z}_i = \{T_i \quad C_i \quad R_{ij}C_i \quad \Phi_{dist,i}/C_i\}^T \tag{22}$$

The input vector $\boldsymbol{u}_i$ is:

$$\boldsymbol{u}_i = \{T_j \quad \Phi_{HVAC,i} \quad \Phi_{solar,i}\}^T \tag{23}$$

The measured output is $y_i = T_i$. The discretized state equation of a single EKF is written by using the explicit Euler method (the subscript i referring to the i-th thermal zone is omitted):

$$\begin{Bmatrix} T_k \\ C_k \\ (R_jC)_k \\ (\Phi_{dist}/C)_k \end{Bmatrix} = \begin{Bmatrix} T_{k-1} + \Delta t \left(\sum_j \frac{T_{j,k-1} - T_{k-1}}{(R_jC)_{k-1}} + \frac{\Phi_{HVAC,k-1}}{C_{k-1}} + \frac{\Phi_{solar,k-1}}{C_{k-1}} + (\Phi_{dist}/C)_{k-1} \right) \\ C_{k-1} \\ (R_jC)_{k-1} \\ (\Phi_{dist}/C)_{k-1} \end{Bmatrix} \tag{24}$$

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where k is the time index. Despite the values of the unknowns at time k are assumed equal to the previous values at time $k-1$, it is possible to trace their trend thanks to the probabilistic component of the algorithm.
Practical implementation of Kalman filters is often difficult due to the proper tuning of the noise covariances $\boldsymbol{R}$ and $\boldsymbol{Q}$, that are usually built as diagonal matrices (noises are uncorrelated). The measurement noise $\boldsymbol{v}$ depends on the accuracy of the measure, therefore on the quality of the temperature sensors. Covariance $\boldsymbol{Q}$ quantifies uncertainties due to model approximations. Process noise for temperatures T_i is correlated with the accuracy of the state equation: the more the law is detailed, the smaller the noise value. As nothing is specified on the evolution of the unknowns, the corresponding variances must be greater than the others, so that the filter can identify their value over time. The noise level for RC parameters should be much smaller than for disturbances $\Phi_{dist,i}$, because RC values are constant, while $\Phi_{dist,i}$ varies over time. High values in matrix $\boldsymbol{R}$ and small values in matrix $\boldsymbol{Q}$ means that the state model is trusted more than measurements and vice versa. The right trade-off between the two covariances must be found.
The whole procedure is divided in two parts:

- Training phase
  State models and EKFs are connected and run in real time. Indoor air temperatures T_i are measured; outdoor temperature T_{out}, solar heat gains $\Phi_{solar,i}$ and HVAC system gains $\Phi_{HVAC,i}$ are considered as input. Unknown thermal parameters R_{ij} and C_i and unknown heat gains $\Phi_{dist,i}$ are identified.
- Prediction phase
  Identified thermal parameters R_{ij} and C_i are introduced in the state models, that are used without the EKFs to predict the behaviour of the real system during the next days / weeks. Outdoor temperature T_{out} and solar heat gains $\Phi_{solar,i}$ are considered as input, they should be assumed. Disturbances $\Phi_{dist,i}$ are considered as input and are assumed to be proportional to the values estimated in the training phase.
  A) By imposing a specific scheduling of the HVAC systems, it is possible to predict the indoor temperature profile of the bodyshop.
  B) By imposing a desired indoor temperature profile, it is possible to produce a forecast of the required heating load $\Phi_{HVAC,i}$ of the building and plan the scheduling of the HVAC systems.

Since the heating load is the thermal power supplied to maintain the temperature in the building, this forecasting allows to determine an estimation of the energy consumption for heating. If further data is provided regarding the heat gains / losses that have been grouped into $\Phi_{dist,i}$, the results of the prediction can be improved by increasing the level of detail of the equivalent RC model.
The proposed methodology can be implemented in numeric computing environments, such as MATLAB and Python.

5.3. Integrated approach for system description and statistical-deterministic analysis

The RFLP approach allows defining a set of requirements the target system should comply with, integrating models which describe the target system and verifying the fulfilment of the initially defined requirements. It is possible to trace the path from a requirement to the logical solution used to guarantee that requirement and vice versa. It follows that the modelling of system physics through a statistical and/or deterministic approach (for monitoring, forecasting and reduction of consumption) can be carried out in a coherent and consistent way with the initial set of requirements.
Considering the industry/factory framework, energy flows can concern different levels, such as: a) devices for production purposes, e.g., electric equipment/motors; b) process heating and cooling; c) air/space conditioning; d) energy production, *e.g.*, heat pumps, co- and tri-generation plants.
The potential of energy optimization regarding levels *a)* and *b)* is quite limited because the operation of such devices is generally ruled by processing data and production targets. On the other hand, there is large room for optimization as concerns levels *c)* and *d)* with regards to both design and

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operation/regulation. In this regard, referring to the CRF use case, the painting process of car body has been identified as one of the most energy intensive process. Focusing on the sub issue related to the car body topcoating, it emerges that the AHU (Air Handling Unit) of topcoat booth is the most energy demanding utility. In this context, the identified problem can be described and analysed systematically and consistently by means of the RFLP approach. As shown in Figure 26, the set of requirements related to the AHU system can be defined in a hierarchical form starting from the global mission of the system: *"The system should assure air conditioning"*; *"The system should deal with thermoregulation, ventilation, air quality management, humidity management"*; *"The system should assure dry-bulb temperature from 20.5°C to 25.5 °C"*; and so on towards a greater degree of detail.
An overall function, and then a set of sub-function, should be related to each requirement: *"Space (topcoat booth) conditioning"* as overall function and then *"Air Heating/Cooling"*, *"Air filtering"*, *"Air recirculation"*, and so on as sub-function. The definition of the functional architecture derives the identification of the logical solution: the logical components, e.g., *heating coil*, *cooling coil*, *filters*, *ducts (intake and exhaust)*, implement the previously defined requirements. Then, the statistical and deterministic models are used to simulate the system behaviour and finally, a testing phase allows verifying the fulfilment of each requirement.

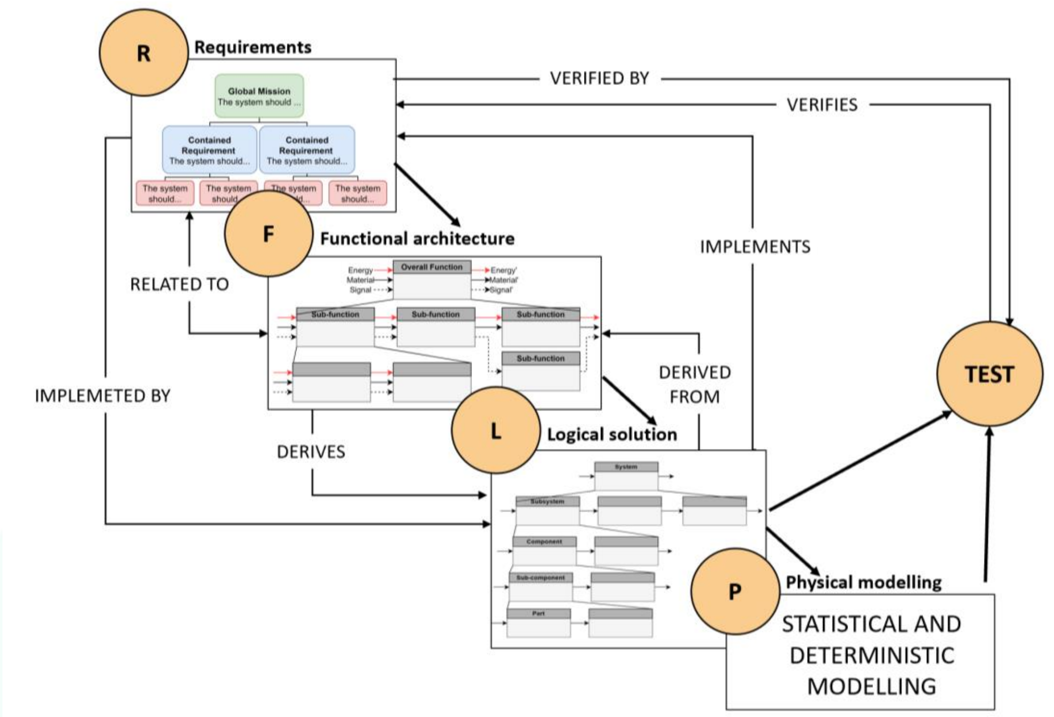

Figure 26. RFLP approach for system description and analysis.

An example building was investigated in order to assess potential energy savings, that can be achieved combining RFLP approach, white box models, artificial intelligence and model predictive control (MPC) [64]. This study applies a simulation- and optimization-based framework using artificial neural networks for the MPC of space heating systems. Accordingly, it investigates machine learning techniques to predict energy performance of a real building. The framework is envisioned to provide optimal values of setpoint temperatures on a day-ahead planning horizon to minimize energy cost and thermal discomfort, based on weather forecasts. The setpoint requirements, the related functional and logical solution could be defined by means the RFLP approach, as shown above. A Pareto multi-objective approach is applied, modelling thermal comfort via the adaptive theory of ASHRAE Standard 55, *i.e.*, assessing a comfort penalty function. The optimization problem is solved by running a genetic algorithm – variant of NSGA II – under MATLAB® environment. The objective functions are assessed via the coupling between MATLAB® and EnergyPlus, used as building performance simulation tool. The multi-criteria decision-making is performed by setting a limit to comfort penalty to pick an optimal solution from the Pareto front. The framework is tested addressing a typical day of the winter season

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and using EnergyPlus weather data to simulate weather forecasts. Compared to a reference control at a fixed setpoint – 21°C – the proposed solution with similar comfort performance ensures daily cost savings of around 9%. Such results show that sustainable building design is not sufficient if not coupled with optimized control. Besides the proposed virtual implementation, the framework can be integrated into automation systems for real-time MPC at the building level, as well as at an industry/factory level.

Furthermore, the use of the functional data analysis approach described in Section 3.2.2 is proposed for the one-day-ahead forecasting of the energy consumption daily curves. The Paintshop use case, subtask 2, i.e., air handling unit (AHU) of topcoat booth is the considered use case. The data set contains measurements of the actual power consumption, measured in kWh, as well as temperatures, relative humidity, flow rate, and many other variables. Among the power consumption variables, we focus on the prediction of the variable identified by the column "P_AHU_REAL_HOT [kWh](16)", which is the power necessary to heat the indoor air of the booth to keep regulated condition of temperature and humidity. While the regulation of temperature and humidity requires both heating and cooling, in this case we focus on forecasting the power consumption for heating only, since it requires more power with respect to cooling. Unfortunately, while the entire data set refers to a relatively long period, i.e., about 15 months, the data relative to the power consumption are available only for a shorter period, i.e., the first 3 months. For this reason, we show the results obtained over this shorter period and we illustrate the results that are potentially achievable if more information is available.

We model the daily profile of the power consumption y(t) observed over the daily temporal interval T on day k as: $y_k(t) = f\left(x_{k1}(s), \dots, x_{kp}(s)\right) + \varepsilon_k(t),\ s \in S, t \in T$, where $x_{k1}, \dots, x_{kp}$ are functional covariates, i.e., the daily profiles of other variables that are expected to have an influence on the power consumption and $\varepsilon_k(t)$ is the error term. Since we are interested in forecasting, actually the functional covariates are observations of variables up to the previous day. A selection phase led us to a linear model where the functional covariates include an autoregressive component of order one, i.e. $y_{k-1}(s)$, while the other chosen covariates are selected as the columns “"Qv_H2O_HOT_PRE [m^3/h](21)", "T_booth [°C](24)", "T_in_HOT_PRE [°C](28)”, "T_OUT [°C](29)" , "T_RA [°C](33)", and "T_SA_REAL [°C](35)" of the dataset, all observed on the previous day. Moreover, we assume the relationship f to be linear, then we estimate the following model $y_k(t) = \beta_0(t) + \sum_{j=1}^{p} \int_S x_{k-1,j}(s)\beta_j(s)ds + \varepsilon_k(t)$.

The model is estimated using [24] and the R package funcharts [65]. Figure 27 shows the daily profiles of the power consumption due to heating against its one-day-ahead forecast, over a time horizon of the last month. We can see two main behaviours over different days. Some days show a low power consumption, other days show a high-power consumption. For this reason, we used two different models depending on the average value of the power consumption of the day. We assume that we know in advance one day ahead if, on the following day, the consumption is high or low. This means that, for days with low (high) consumption, the prediction is made using, as historical data set, the power consumption daily profiles observed on all previous days where the consumption was also low (high).

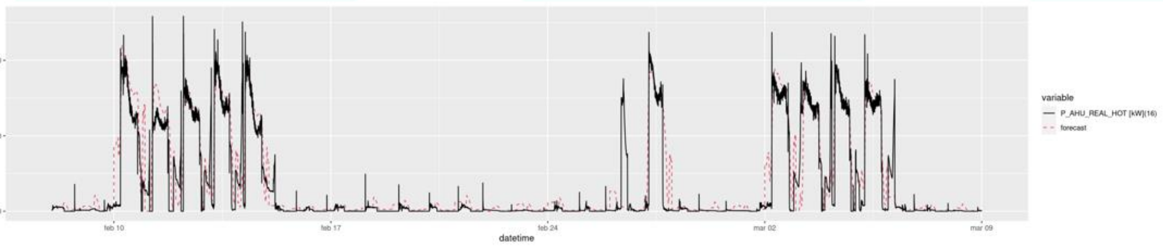

Figure 27.Daily profiles of the power consumption due to heating (black solid line) against its one-day-ahead forecast (red dashed line).

Given that the proposed functional model is designed to work with complex data such as daily consumption profiles, we expect the prediction performance of our approach to improve with

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increasing sample size. This model can be improved by integrating the other variables about temperatures, relative humidity, flow rate or by considering non linearities. Moreover, status variables are also available that can help in distinguishing the different operational modes. To evaluate the forecasts while taking overfitting into account, for each k-th day we estimate the proposed functional autoregressive model using the data from the previous k days and then we evaluate the prediction error on the k-th day. By iterating this over all the days, we obtain forecasts that are not affected by overfitting. We evaluate the one-day-ahead forecasts based on the root mean squared error (RMSE) and the mean absolute error (MAE) metrics. We obtained RMSE=154 kWh and MAE=75 kWh. These results are only a starting point and are expected to be significantly improved once more data are available and information on the other variables is appropriately integrated. Once a more accurate model is fit, control charts can also be built to monitor the process and identify anomalous daily profiles. To show the potential application of statistical process monitoring to the power consumption daily profiles, Figure 28 shows a control chart built based on the methodology proposed by [23]. Two control charts are used simultaneously to monitor each daily profile, i.e., the Hotelling's T^2 and the squared prediction error (SPE) control charts, which are shown in Figure 28. Points correspond to the monitoring statistics, while segments are the upper control limits, which vary from day to day because the estimation is updated after each day. This means that each daily profile is monitored simultaneously by the two control charts. If, for a given day, one monitoring statistic is above its upper control limit in at least one of the two control charts, the observation is signalled as anomalous. As an example, the 35-th observation is signalled as anomalous and in Figure 29 the corresponding profile is the only one where the power consumption is above 400 kW during the entire day. This is also a starting point only, because better modelling will lead to more powerful control charts, able to better distinguish anomalous daily patterns from normal variability.

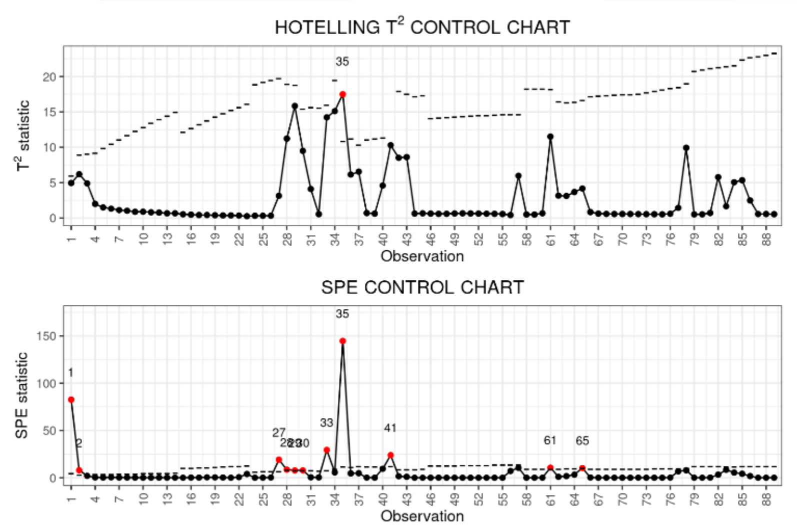

Figure 28. Control chart for monitoring the daily consumption profiles.

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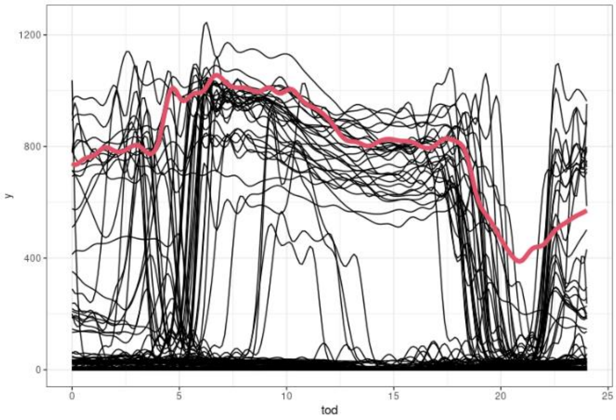

Figure 29. Power consumption daily profile n. 35 signaled as out of control by the control charts in Figure 28. The profile is plotted in red against all the other daily profiles, plotted in black.

5.4. Energy market prediction (preliminary results about energy market trends)

The electricity price exhibits strong fluctuations from day to day for all European energy markets, as it is derived as a result of the market-clearing procedure. In this procedure, the two main subsets of market actors involved, power producers and power consumers, affect significantly the day-ahead market price. For ensuring an as accurate as possible prediction, it is necessary to identify and analyse the main factors influencing the electricity price, which will be part of forecasting models' input [35], [66]. Towards this direction, in the following, the required list of these inputs is first identified followed by some preliminary results stemming from the implementation of a hybrid price forecasting model [33, 67].

On one hand, the cost of energy generation differs between the various power producers. To begin with, renewable power units are an indispensable and low-cost part of energy system nowadays [68] forming a sustainable and environmentally friendly energy solution. However, this solution and more specifically the generation through solar and wind is inextricably linked to the current weather conditions. As long as electricity energy cannot be stored, the forecasted day-ahead amount of generation from solar and wind sources should be taken into consideration. Additionally, another factor that affects the price is the predicted day-ahead amount of energy generation. This amount determines not only the percentage of participation of RES (Renewable Energy Sources) in the source mix, but also the corresponding percentage of the conventional energy sources, such as coal and gas-fired power plants. Their operational limitations and their connection with the financial markets due to the raw material required, increase the respective cost of energy. For example, the rocketing of the natural gas price has soared the cost of energy generated by gas-fired power plants. Moreover, carbon emission allowances under the EU Emissions Trading Scheme (ETS) further increases the cost of conventional power units in an effort to reduce society's energy footprint. Finally, in Europe, day-ahead markets are coupled, creating a single pan European cross zonal day-ahead electricity market. In an attempt to increase the overall efficiency, integrated day-ahead markets were introduced. In this way, bidding-zones are created, in which countries can exchange energy [69, 70, 71]. As a result, the corresponding load quantities must be taken into account too.

On the other hand, from the perspective of power demands, large consumers and retailers play a key role [68]. Regarding the first category, industrial plants adhere to a specific time schedule through the days of a year. As for the second category, retailers sell the power to a large number of small-scale demands, e.g., households. It is known that under normal conditions, both industrial plants and small-scale demands, follow a pattern regarding their energy consumption. This pattern can be characterised by its seasonality in the sense that the energy demand in holidays, working days, weekdays etc. experience regular and predictable changes that recur every calendar year. Another

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parameter that affects this pattern is weather. Temperature, wind speed and solar radiation can alter industrial processes as well as the habits of individuals, thus changing their energy demand. In the case of a factory, if it is necessary for the temperature of a part of the production to differ significantly from the ambient temperatures, significant amounts of energy will be expended, while a similar situation can be found in a household. Extending this example to a larger scale, highlights the need to integrate weather data into the input of the prediction models. However, at the country level, this data should be limited to the most energy-intensive areas, i.e., the big cities. At last, the input must include not only specific variables for the load demanded, but also the respective forecasted day-ahead load demanded and the actual load of the previous days.
In conclusion, the complexity of the energy price forecasting problem demands a multivariable input in an effort to increase accuracy. For the aforementioned reasons the basic list of inputs are:

1. **Electric energy production data per energy market supported**
   a) Day ahead historical predictions
   b) Realised historical production
   c) Connected energy markets predictions if available (e.g., TTF gas market prices)
   d) Published energy production estimations
2. **Electric energy demand data per energy market supported**
   a) Day ahead historical predictions
   b) Realised historical consumption
   c) Connected energy markets predictions if available
   d) Published energy demand by energy market operator
3. **System Marginal Prices per energy market supported**
   a) Day ahead historical predictions
   b) Realised historical SMP
   c) Connected energy markets SMP if available
4. **Weather data**
   a) Temperature, wind speed, solar radiation etc.
   b) outside temperature, relative humidity, etc.
5. **Miscellaneous data**
   a) Holidays, working days, weekdays, year period

During the first phase of the implementation performed by the UoP team towards (electricity) price forecasting, a subset of the desirable inputs, which can be sourced from publicly available data sources, was used. Several forecasting algorithms were deployed, such as regression methods (OLS, Ridge, Lasso), Tree based methods (Random Forest) and RNN ones (LSTM), [71, 72]. Through the observation of their performance, it can be noted that some of the algorithms are more responsive to price spikes, while others turn to biased estimations of the forecasting accuracy. This has led to the combination of multiple forecasting algorithms created a hybrid ensemble prediction model that exhibits a more robust performance compared to individual ones. Figure 30 presents the features importance implementing such an ensemble model for the prediction of the energy prices. It can be observed that due to the current variability in the behaviour of the energy market players the most important feature component is the last 7 days prices. Evidently, the significance of the various components has changed due to the new structure of the energy markets.

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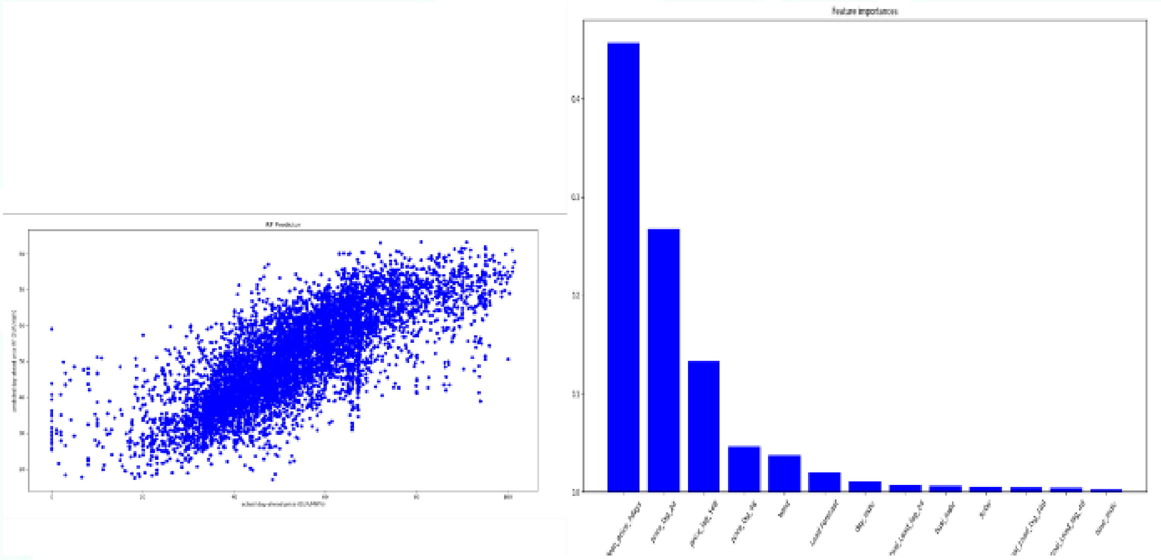

Figure 30. Hybrid Energy Market Price Forecasting.

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6. CONCLUSIONS, OUTLOOK AND NEXT STEPS

6.1. Outcomes & conclusion

The work performed proposes methodologies and tools designed for the modelling used in digital twins and for different model levels, from the component to the whole machine, value chain, workshop area or plant.

At the component scale, a non-exhaustive elementary model library is proposed for energy conversion devices, such actuators, heaters, rotating machines, etc. The elementary models are classified and defined in terms of physic field, goal, input, and output. The set of proposed models concerns rotational and translational mechanical systems, electrical systems, fluid systems and thermodynamic systems.

The assembly of described models is defined in a Model Based Systems Engineering approach. The complete architecture comes from a concept of value stream framework that structures the resulting meta-models in a Requirement, Functional, Logical, Physical (RFLP) approach. Analytical descriptions of models and Key Performance Indicators are all targeted towards energy in order to verify and control in each model energy flows. In order to assess potential energy savings, RFLP approach, white box models, artificial intelligence and model predictive control (MPC) are combined and illustrated through the example of an industrial building.

In other words, the connection with the real word is performed by means of digital twins and in the Kalman filter theorical framework. This approach allows also a stochastic description based on Bayesian assumptions and leads to prediction tools of uncertainties in dynamic systems. The complete approach is described with reference to the CRF Bodyshop use case. This use case mainly regards the thermodynamics of a large workshop and can be used as a starting point for other applications.

6.2. Outlook & next steps

Some developments are in progress and will complete the work described in this document by promoting interactions with other tasks and work packages:
- different and detailled simulation process of the bodyshop (use case CRF) with real or fictive data (meteorological, production, etc.)
- the application of the proposed method for a use case including a larger set of physics and components
- improvement of the first results (on non-residential building) with larger and longer sets of data
- the development of tools able to ensure an efficient link between simulation tools and co-simulations workflow.
- interaction with other connected deliverables (D4.2, D4.3, WP5, WP6).

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement **No 958478**

APPENDIX A: HIERARCHICAL LEVELS IN SCIENTIFIC LITERATURE AND INTERNATIONAL STANDARDS

Wiendahl et al.	Sauer	Alvandi et al.	Merschak et al.	Mousavi et al.	Francalanza et al.	Jackson and Jones	Heinemann et al.	ISA-88	IEC61512 1:2000	IEC62264-1
Network	Company level		CPPS-Level					Enterprise	Enterprise	Enterprise
Site	Plant/shop level	Factory level	Factory-level	Factory	Factory	Facility	Plant	Site	Site	Site
Segment		Process chain level			CPPS	Machining/ assembly shop	Production area	Area	Area	Area
System			System-level	Process chains		Virtual cell	Production system			Work center
Cell	Cell level					Workstation	Manufacturing cell	Process cell	Process cell	
Station		Unit process level			Machine	Machines	Workstation	Unit	Unit	Work unit
			Module-level	Machine tool				Equipment module	Equipment module	
	Field level							Control module	Control module	
		Component level	Component-level						Control unit	
Processes										

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APPENDIX B: COLLECTION OF ENERMAN RELATED MODELS

Collection of EnerMan energy related models Version 31.12.2021 (FHOOE)

		Metadata			
	Modelname	Superordinate collection [Optional]	Systemlevel	Relevant aspect for EnerMan	Type
1	**Core-Auxiliary Component Split**		Component	Identification of core operations	Structure
2	**Circumstance dependent power profile**		Component	Representation of energy consumption	Behaviour
3	**Energy breakdown diagram**		Unbound	Visualization of main energy drivers	Description & Visualization
4	**Unit process boundary description**		Unbound	Quantification of impact on eco sphere	Process
5	**Time distribution diagram**		Unbound	Visualization of time spent	Description & Visualization
6	**Process power profile**		Component	Identfication of peak loads	Behaviour
7	**Parameter energy mapping**		Component	Parameter and state dependant energy consumption	Behaviour
8	**Energy process chain modelling**		Production Line	Energetic production system description	Structure
9	**Process based energy consumption**		Unbound	Calculation of total energy used	Other
10	**State Machine**	SysML	Unbound	General model of enery bounded state transitions	Behaviour
11	**Discrete event simulation model**		Unbound	Abstracted simulation of resource utilisation	Behaviour
12	**Value stream map**		Value stream	Identification of wasteful operations and bottlenecks	Process
13	**Customer-value based process model**		Value stream	Abstracted description for DES and VSM	Description & Visualization
14	**Resource availability description**		Unbound	Abstracted description for DES	Description & Visualization
15	**Analytical model**		Component	Mathematical physical description of the energy related syst	Behaviour
16	**Data clustering algorithms**		Unbound	Extract energy relevant features from measurement data	Other
17	**Thermodynamic model**		Component	Thermodynamic description of the energy related system	Behaviour
18	**Hydraulic model**		Component	Hydraulic description of the energy related system	Behaviour
19	**Electrical model**		Component	Electrical description of the energy related system	Behaviour
20	**Dynamic model**		Component	Dynamic description of the energy related system	Behaviour
21	**Data processing and filtering algorithms**		Unbound	Enhance data quality of energy related measurement data	Other
22	**Deterministic model**		Unbound	Aggregate numercial simulations for KPI calculation	
23	**Resource related cost model**		Unbound	Determination of various cost types (CO2eq, Financial)	Other
24	**Energy conversion model**		Component	Describe conversion losses between energy types	Description & Visualization
25	**Energy consumtion prediction model**		Unbound	Predict future energy consumption	Process
26	**Energy flow model**		Unbound	Visualization of energy types and processes	Description & Visualization
27	**Consumed energy cost prediction**		Unbound	Predict future energy consumption	Process
28	**Degree of effectiveness model**		Component	Indicator for energy efficiency	Behaviour
29	**Fluid dynamic model**		Component	Fluid dynamic description of the energy related system	Behaviour

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	Model data		
	Information input	**Information output**	**Physical effect/domain [Optional]**
1	List of components	Grouped components	
2	Circumstance, component characteristics	Power consumption of components	
3	Energy consumption	Visualization	
4	Semi finished product, Materials, Electricity, Compressed Air, Process Materials,	Gaseous Emissions, Liquid Emissions, Solid Emissions, Heat, (Recycleable)	
5	Time spent in activity	Relative time influence	
6	Consumed energy by component, component states	Consumed energy by process	
7	Parameters states, Mapping curve	Consumed energy by component	
8	Energy and material flow entering the system, Manufacturing process chains	Products, Waste energy	
9	State-specific energy consumption	Total process energy consumpiton	
10	States and transition conditions, Input events	State and transisiton output, Events	
11	Resource availability, process order and description	Bottlenecks, lead times, ressource utilization	
12	Process order and description, lead times	Value-adding activities, bottlenecks	
13	Customer cycle, processing times	Needed capacities	
14	Production data aquisition, estimates	Availabilty, Failure distribution	
15	Physical fundamentals, Parameters	Mathematical description model	
16	Measurement data	Energy relevant feature regions	
17	System specification	Physical fundamental	Thermodynamic
18	System specification	Physical fundamental	Hydraulic
19	System specification	Physical fundamental	Electrical
20	System specification	Physical fundamental	Dynamic
21	Measurement data, filter parameters	Filtered measurement data	
22	Numerical simulation models, targeted KPI	KPI	
23	Energy costs, resource status	cost model	
24	Degree of effectiveness	resulting energy types and quantities	
25	Energy conversion properties, degree of effectiveness, Process parameters	Time dependant energy consumption	
26	Process order and description, energy conversion per process	Visualization (e.g. multi level Sankey) of energy types and conversions	
27	Energy consumption prediction, energy cost prediction	Time dependant incurring costs	
28	Deterministic model	Degree of effectiveness	
29	System specification	Physical fundamental	Fluid dynamic

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	Scope of validity	Activity	Sensor interfacing	Partner	Additional References [Optional]
1	All domains, unrestricted	Split in auxliary and core component	No	FHOOE	Triebe 2018
2	All domains, restricted	Get power consumption based on	Yes	FHOOE	Triebe 2018
3	All domains, unrestricted	Visualize major energy consumers	Possible	FHOOE	Triebe 2018
4	All domains, restricted	Map techno-sphere inputs to techno- and	No	FHOOE	Duflou 2012
5	All domains, unrestricted	Visualize process times of core and	Possible	FHOOE	Duflou 2012
6	All domains, restricted	Map consumed component energy to	Possible	FHOOE	Duflou 2012, Li 2017
7	Reduced domains, restricted	Map component parameters to	Possible	FHOOE	Duflou 2012
8	All domains, restricted	Map energy to materials and processes	No	FHOOE	Duflou 2012
9	Reduced domains, restricted	Get energy consumption from system state	No	FHOOE	Li 2017
10	All domains, unrestricted	Get system state from input events	Yes	FHOOE	
11	Reduced domains, restricted	Identify resource utilisation from jobs	Possible	SIMPLAN	
12	Reduced domains, unrestricted	Identify lean potential and bottlenecks	Possible	SIMPLAN	
13	Reduced domains, unrestricted	Get needed resource capacities	Possible	SIMPLAN	
14	Reduced domains, restricted	Get numerical/availability of resource	Possible	SIMPLAN	
15	All domains, restricted	Describe system with physical fundamentals	Possible	SUPM	
16	All domains, unrestricted	Transform measurement data to feature sp	Yes	SUPM, UNINA	
17	Reduced domains, restricted	Describe system with thermodynamic mode	Possible	SUPM, UNINA	
18	Reduced domains, restricted	Describe system with hydraulic model	Possible	SUPM, UNINA	
19	Reduced domains, restricted	Describe system with electrical model	Possible	SUPM, UNINA	
20	Reduced domains, restricted	Describe system with dynamic model	Possible	SUPM, UNINA	
21	All domains, unrestricted	Reduction or removal of artifacts	Yes	SUPM	
22	All domains, restricted	Aggregate numercial simulations for KPI calculation		UNINA	
23	All domains, restricted	Determine various cost types (CO2eq, Finan	Possible	FHOOE, Proposal	
24	Reduced domains, restricted	Describe conversion losses between energy	No	FHOOE	
25	Reduced domains, restricted	Predict future energy consumption	Yes	FHOOE	
26	All domains, restricted	Visualization of energy types and processes	Possible	FHOOE	
27	All domains, restricted	Predict future energy consumption	Possible	FHOOE	
28	All domains, restricted	Indicate energy efficiency	Possible	FHOOE	
29	All domains, restricted	Describe system with fluid dynamic model	Possible	UNINA	

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