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Digital Energy Twin
Optimised Operation and Design of Industrial Energy Systems

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Digital Energy Twin

Optimised Operation and Design of Industrial Energy Systems

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1 Introduction

Industrial energy systems in the manufacturing sector are traditionally designed around single supply technologies, often lacking adaptability to fluctuations in energy demand and supply. Consequently, their ability to respond to dynamic shifts in both thermal and electric demands is limited. Recognizing this limitation underscores the need for optimal support in fine-tuning the operation of industrial energy systems, considering the niceties of both energy demand and supply aspects. From this, the need for the best possible support in optimizing the operation of the industrial energy system (demand and supply), the interaction of different renewable (volatile) and conventional energy sources and the design for industrial energy systems can be derived.
In the context of the printed circuit board (PCB) industry, where there is a persistent upward trajectory in product demand, companies like AT&S in Austria are confronted with the dual challenge of expanding production capacity while simultaneously adapting to evolving end-user requirements. This continual adaptation triggers substantial fluctuations in energy demand and supply, thereby imposing constraints on energy capacity limits at the site. The inherent flexibility of the industrial energy system makes it exceedingly challenging for the industry to proactively plan and evaluate necessary adaptations and investments in both the processes and energy supply systems. Turning to future challenges, it is clear that this complexity will increase in the coming years.

1.1 Aims of the project

The primary objective of Digital Energy Twin is to contribute to industrial advancements by devising a methodological framework and simulation models for the enhancement of operational efficiency and design optimization within industrial energy systems. The central focus of the project is on the formulation of comprehensive optimization approaches, based on real-life production data, historical records, and predictive analyses pertaining to the existing system. This approach considers both the process energy demand and the energy supply side. The following specific goals were addressed by project:

1. Optimised operation and design of industrial energy systems (Section 2.1.4)
    - A generalized optimization combining energy demand on process level and energy supply has been established.
    - A control strategy based on optimization was realized at lab scale
    - Energy system design optimization based on historic data was established
2. DigitalEnergyTwin - Application of digital twin methodology to industrial energy systems (Section 2.2.5)
    - The operational optimization concept based on a simplified version of the full energy system of company AT&S was defined and tested
    - A prototype of a Digital Energy Twin at lab scale was developed. This prototype showcases realtime control strategies which are not applicable in productive industrial environment at the moment.
    - Security measures to counter attack vectors have been evaluated.
3. Validation of the DigitalEnergyTwin by real-life implementation in industry
    - Modelling of complex (renewable and conventional) energy system by functional combination of energy demand and supply in manufacturing industry was established
    - Real-life implementation in industry was partly established. The digital models and algorithms were demonstrated in an off-site laboratory environment. Models are able to run also on-site.
    - The results of the Digital Twin prototype at the digital factory at FHV are validated with real-life data from the laboratory process regarding the energy consumption of its devices.
4. Impact maximisation by standardisation and simplification

- The FMU (Functional Mock-up Unit)-Standard was used throughout the project for standardised model exchange.
- Simplification of complex industrial energy system models using methods of model order reduction (MOR) was included.

5. Exploitation of DigitalEnergyTwin
    - Product derivation based on business model canvas method
    - E-learning and Training for employees and experts was established by development of virtual reality VR training workflow

1.2 Classification in the research program

The project focuses on the topic area 3 of the 2018 Energy Research Program "Industrial Energy Systems" with a dedicated emphasis on "Digitization aspects of industrial hybrid networks".[1] The primary objective of the project was the conception, developed and demonstration of Digital Energy Twins of the energy demand and supply of production processes. The development was conducted both on a laboratory scale and within a genuine, industrially relevant environment.

The DigitalEnergyTwin project advanced the state of the art through research, development and implementation of an optimisation approach for the heat and power supply of industrial energy systems. Both, operational and design optimization of energy systems were elaborated, and production schedules were considered. Industrial relevance of the developed models and algorithms was showcased by considering highly relevant industrial data and production schedules. Using AR/VR technologies for visualization purposes, results are immersive and are used for innovative operation monitoring and training.

1.3 Methods used within the work

The methodical approach starts with the analysis of the industrial framework conditions at the application partner AT&S. Literature research on modeling, simulation, optimization, and the general application of digital twins in the manufacturing industry formed the basis for further developments. More specifically, specific requirements were derived from literature research and from knowledge of partners. Methods for the development of a Digital Energy Twin thereby were identified to support functional mock-up interfaces (FMI) for co-simulation. Modelica language was used for physical modelling, Python language was used for data-driven modelling. Time series forecasting machine learning models were used for the prediction of the overall energy consmption. Here, Long Short Term Memory Neural Network (LSTM) with manual feature engineering and LSTM with Convolutional-Layers for feature extraction were integrated and compared.

The results have been achieved by the establishment of two distinct usecases:

- A lab-scale Digital Energy Twin prototype at FH Vorarlberg to demonstrate and analyse real-time functionalities and online control by an online Digital Twin of the production system (see section 2.2)
- A Digital Energy Twin framework on industrial scale considering the site of AT&S in Leoben, demonstrating real-scale modules of a Digital Twin within a restricted run-time environment, decoupled from the industrial site (see section 2.3)

1 https://www.ffg.at/sites/default/files/allgemeine_downloads/thematische%20programme/Energie/leitfaden_energieforschung_2018_rz.pdf

The method of having these two approaches available for the development supported the successful demonstration of real-time twinning applications (on lab scale) and enabled a comprehensive view on the problems and possibilities, the implementation of a Digital Energy Twin on industrial scale does have.
The validation of the simulation and optimization models was done based on measured and external data from both usecases. The validation of the industrial usecase was performed on a specific part of the AT&S site (Werk I) only to reduce its effort.
Visualization of energy data and information was performed used methods of Augemented and Virtual Reality (AR/VR). Various devices were considered and tested while the results were available for Microsoft HoloLens (AR) and various VR devices that are compatible with the OpenXR API.
SWOT-Analyses and questionnaires have been used to support the development of business cases for Digital Twin applications and to derive products. Finally, a business model canvas was developed by the project partners to identify value propositions and how they can be addressed and installed.
The project results were published via various channels (social media, newsletter, website), academic publications, journal articles, workshops, webinars and conference presentations and communicated to interested stakeholders.

1.4 Structure of the work

Section 1 is about the aims of the project, the classification in the research program and the methods used within the work.
Section 2 deals with the technical description of the project content. In more detail, in section 2.1 the Digital Energy Twin concept and its requirements are presented. Co-Simulation, physical modelling of the usecases, Data-driven modelling of specific manufacturing processes, and optimization methods are within the scope of this section. Section 2.2 presents the lab scale use case “digital factory” at FH Vorarlberg. The used methods regarding boundary conditions, modelling and optimization of the energy demand and supply of the manufacturing configuration including industrial robots are described. Section 2.3 presents the industrial use case “AT&S”. The framework of the digital shadow concept is described and both physical and data-based models are presented. The models and algorithms for the operational optimization of the energy supply are detailed. Further, three studies regarding the design optimization of the heat supply network are presented. In section 2.4 and section 2.5, visualization based on augmented reality (AR) and virtual reality (VR) is described. The different concepts of immersive visualization finalize this research work.
The main results and conclusions are summarized in chapter 3.
Chapter 4 closes with an outlook and recommendations.

2 Description of project content and results

The methodology of the digital twin is developed and applied to the controlled environment of a lab (specifically, the digital factory in Vorarlberg) and an operational PCB and IC substrate manufacturing industry (AT&S's plant in Hinterberg). This dual-use case approach serves to underscore the advantages of working on a lab scale, where restrictions are minimal, and challenges are mainly of a technical nature. Conversely, it highlights the unique challenges encountered when transitioning to an actual industry setting. These challenges include, but are not limited to, lower data quality, heightened security concerns, and the necessity to engage multiple departments due to the distributed knowledge about the system. By adopting this comprehensive strategy, the focus is not only on refining the digital twin's setup, methods, and technical aspects but also on effectively tackling the intricate challenges inherent in its implementation within an industrial context.
The project deals with main aspects of a digital twin for the energy supply and energy consumption of industrial systems. These are the framework of the digital twin itself, the model's development and validation, handling, and management of data with focus on security, optimization methods, implementation of the digital twin, and advanced visualization techniques like virtual and augmented reality.

2.1 The Digital Energy Twin concept and its requirements

A literature review was conducted to categorize different existing digital twin implementations, with a particular focus on the manufacturing industry. The survey papers published by Negri et al.[2] and Kritzinger et al.[3] comprehensively define and classify the Digital Twins (DT) implementation in industrial and manufacturing fields. Current literature mainly consists of concept papers without concrete applied case-studies. A focus of recent research concerning the DT in manufacturing is dealing with production planning and control as it is a main data-sink within a production system that ties everything together. Hence, it has a mid-level time-horizon, simulation is often used to exploit the models at their best.

Next, requirements of the digital energy twin in regards of modelling, simulation and optimization have been discussed and defined. The following aspects are considered: (i) availability of models, (ii) availability of knowledge in the consortium, (iii) scalability of the models, and (iv) community (academic and practical).

Due to the increasing complexity of systems, evaluating the overall behaviour of industrial energy systems including its processes for different applications (control, design, what-if, etc.) and at different stages of their development is becoming steadily more difficult. To keep benefiting from the results of simulation-based analyses, new techniques are required to efficiently simulate the interactions between different subsystems. There are two ways to achieve this goal: (i) the entire system can be modelled and simulated with a single tool which is referred to as monolithic simulation; or (ii) established tools for the respective subsystems can be coupled in a so-called co-simulation[4]. As our knowledge of each subsystem matures, simulation tools become more specialized, accumulating years of research and practical experience in their respective domains. As such, the use of the co-simulation approach allows existing simulation tools to be leveraged. Thus, co-simulation is very promising in the context of the project.

[2] E. Negri, L. Fumagalli, M. Macchi, "A review of the roles of Digital Twin in CPS-based production systems" in 27th International Conference on Flexible Automation and Intelligent Manufacturing, 2017.

[3] W. Kritzinger, M. Karner, G. Traar, J. Henjes, W. Sihn, „Digital Twin in manufacturing: A categorical literature review and classification" in International Federation of Automatic Control, 2018

[4] Gomes, Cláudio, et al. "Co-simulation: a survey." ACM Computing Surveys (CSUR) 51.3 (2018): 1-33.

2.1.1 Co-Simulation

In co-simulation, the subsystem models are interconnected at their behavioural levels, through the traces computed by the corresponding simulation tools. To run a co-simulation, one needs a co-simulation scenario and an orchestrator algorithm. The co-simulation scenario points to one or more simulation units, describing how the inputs and outputs of their models are related. Each simulation unit is seen as a black box, capable of producing outputs and consuming inputs, according to the model it represents. To produce behavior, the simulation unit needs to have a notion of:

- model, which is created by the modeller based on his knowledge of the system under study;
- solver, which is part of the modelling tool used by the modeller that approximates the behaviour of the model; and
- an input approximation, which approximates the inputs of the model over time, to be used by the solver; as well as
- input reactivity and output reactivity, which determine which inputs the simulation unit receives from the orchestrator.

A recent study on promising standards and tools for co-simulation shows that the Functional Mock-up Interface (FMI) is the most promising standard for co-simulation[5]. The Functional Mock-up Interface is a tool independent standard for co-simulation and the exchange of dynamic models which is currently supported by more than 140 tools[6]. A discussion on research challenges and current barriers of the FMI standard can be found here[7].
Co-simulation methods are applied within the usecase of AT&S, described in section 2.3.6.

2.1.2 Physical modelling

A fundamental distinction in physical modelling can be made between acausal and causal modelling approaches. In causal modelling, the modelled system is described by a system of ordinary differential equations in explicit form. In acausal modelling, the modelled system is expressed as a system of differential algebraic equations in implicit form. Literature shows that acausal modelling techniques are well suited for modelling large-scale multi-domain systems[8]. A literature review shows that Modelica is a promising language since there is an active development community and there is a wealth of (open source) libraries for energy related applications such as energy supply and distribution, HVAC systems or storage technologies[9]. Various Modelica tools support FMI for co-simulation (e.g. Dymola and Open Modelica) and Modelica was previously used by TUG[10], AEE, MUL and FHV. In the context of DigitalEnergyTwin acausal modelling approaches have the following advantages:

- It is simple to read and write physical models[11].

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[5] Schweiger, Gerald, et al. "An empirical survey on co-simulation: Promising standards, challenges and research needs." Simulation modelling practice and theory 95 (2019): 148-163

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

[7] Schweiger, Gerald, et al. "Functional Mock-up Interface: An empirical survey identifies research challenges and current barriers." Proceedings of The American Modelica Conference 2018, October 9-10, Somberg Conference Center, Cambridge MA, USA. No. 154. Linköping University Electronic Press, 2019.

[8] Schweiger, Gerald, et al. "Modeling and simulation of large-scale systems: A systematic comparison of modeling paradigms." Applied Mathematics and Computation 365 (2020): 124713.

[9] Schweiger, Gerald, et al. "District energy systems: Modelling paradigms and general-purpose tools." Energy 164 (2018): 1326-1340.

[10] Schweiger, Gerald, et al. "District heating and cooling systems–Framework for Modelica-based simulation and dynamic optimization." Energy 137 (2017): 566-578.

[11] F. E. Cellier, et al. "Modeling from Physical Principles," in The control Handbook (W.S.Leveine, ed.), 1995.

- The model development time in acausal languages is expected to be five to ten timers shorter compared that for causal languages[12].
- They are well suited for dynamic optimization problems[13].

The physical modelling of the project is described in section 2.3.4.
In addition, in some engineering disciplines MATLAB/Simulink are a preferred tool for modelling, especially for robotic or controller components. They are also capable of exporting FMUs. Since their availability in industrial settings is limited due to a high price tag, Modelica is the preferred choice for DET.

2.1.3 Data-driven modelling

Python is widely used for various applications in data science. It supports state-of-the-art frameworks for data science such as Tensorflow, Keras and Scikit-learn. Furthermore, Python supports FMI for co-simulation and Python was previously used by TUG[14] and FHV for various machine learning applications. Throughout this project, long short-term memory (LSTM) modelling techniques were used to model the usecases (see section 2.2.4 and 2.3.5). For quick prototyping, MATLAB provides useful functionality for machine learning and neural networks, and it also supports FMI standards butit is a highly priced development tool. Therefore, Python is the preferred choice of implementing data driven models in industrial setups.

2.1.4 Optimization

For the operational optimization historical, future/predicted and live (near-real) data. Because input parameters for the optimization like energy demand and energy prices are changing, the optimization must be adapted to these changes. Therefore, a fast calculation of the optimization is needed. The method used to speed up the physical simulation models is described at the end of section 2.3.4.A use case which includes all specific components for the operational optimization has been developed. On this use case different optimization approaches were implemented and evaluated.

2.1.5 Data handling, management and security

The project successfully outlined a secure digital ecosystem and IT architecture for DigitalEnergyTwin applications in manufacturing industries. It involved selecting and adapting efficient data management and processing methods, alongside IT security solutions that balanced cost efficiency and security. The team analyzed existing data sources, structures, and acquisition in industrial processes, focusing on monitoring standards and sensors relevant to DigitalEnergyTwin applications. They defined interfaces with the DigitalEnergyTwin's development environment and outlined representative industrial data handling use cases. Additionally, they conducted a formal risk analysis, developed the IT architecture using unified modelling language (UML), and evaluated data management methods and database systems, ensuring alignment with the project's functional and security requirements.

2.1.6 Summary of requirements

Based on the analysis carried out, see above, the following requirements for the DET are defined,

- Tools for modelling, simulation and optimization must support FMI for co-simulation.

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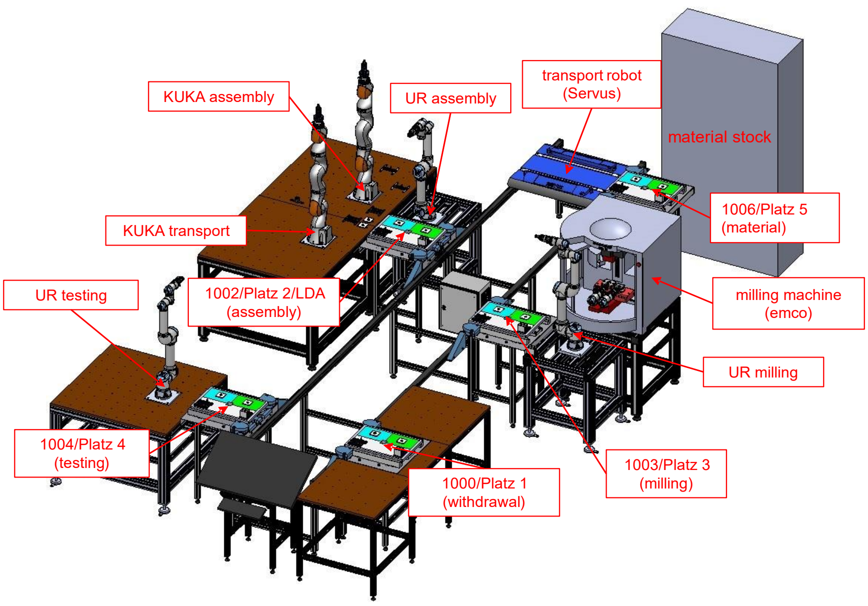
[12] Wetter Michael et al. "Modelica Versus TRNSYS - A Comparison Between an Equation-Based and a Procedural Modeling Language for Building Energy Simulation," in SimBuild, 2006.
[13] Wetter Michael et al., "Equation-based languages – A new paradigm for building energy modeling , simulation and optimization," Energy Build., vol. 117, pp. 290–300, 2016.
[14] Schweiger, Gerald, et al. "The potential of power-to-heat in Swedish district heating systems." Energy 137 (2017): 661-669.

- Modelica is used for physical modelling. Developments should build up on existing (well validated) libraries such as Buildings[15], AixLib[16] or IDEAS[17].
- Python is used for data-driven modelling. Tensorflow is used for various neural networks (CNN, RNN, etc.); Scikit-learn is used for other regression (Decision Tree, Support Vector Regression, etc.) and classification (Nearest Neighbors, Decision Tree, etc.) applications.
- The requirements for the operational optimization are: The global optimum needs to be detected. The energy demand on process level and energy supply must be considered. And energetic, exegetic, economic, technical, and multi-benefit/non-energy-benefit aspects as well as the four pillars in optimization (process, system, integration of renewables, energy exchange over industry boundaries) need to be included. Additionally, a fast finding of the optimum is essential.
- The accuracy of models will be evaluated using a transparent metric[18] consisting of e.g. RMSE, MAE, R2. Furthermore, methods such as Dynamic time warping will be considered when event-based accuracy is relevant.

2.2 Use case digital factory at FH Vorarlberg

2.2.1 The real factory

The main components available in the Digital Factory laboratory are shown in Figure 1. The laboratory consists of 5 collaborative robots (2x KUKA iiwa LBR8, 3x universal robot UR5e), a robotic material transport system (Servus ARC3) and a milling machine (emco concept mill 55).



[15] https://simulationresearch.lbl.gov/modelica/
[16] https://github.com/RWTH-EBC/AixLib
[17] https://github.com/open-ideas/IDEAS
[18] Rätz, Martin, et al. "Automated data-driven modeling of building energy systems via machine learning algorithms." *Energy and Buildings* 202 (2019): 109384.

Figure 1: Setup of digital factory laboratory at FH Vorarlberg

Furthermore, as part of the project a photovoltaic (PV) system and battery storage were integrated within the factory setup for providing flexibility in controlling energy demand provided by the main grid considering environmental and economic circumstances.

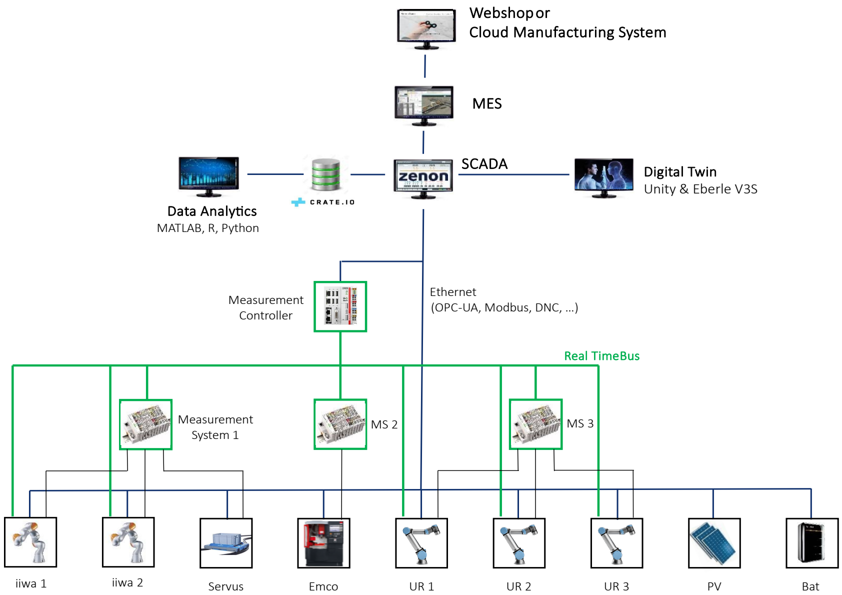


Figure 2: Functional layout of digital factory laboratory

The functional structure of the Digital Factory is shown in Figure 2. Communication between machines and the supervisory control and data acquisition (SCADA) system takes place via standardized industrial communication protocols (OPC-UA, Modbus, DNC, MQTT). Electrical energy data is collected via a measuring system consisting of a central programmable logic controller (PLC), which aggregates and preprocesses the measured values of the decentralized measuring boxes, consisting of a bus interface and power measuring terminals, via a real-time bus and forwards the relevant measured values to a database for further evaluation. To achieve synchronous mapping of time-critical data, e.g., fast robot movements and measured energy values, real-time capable protocols provided by the machinery vendors (FRI, RTDE) are utilized.

2.2.2 DET Framework

The implemented framework for the DET prototype at the digital factory is presented in Figure 3.

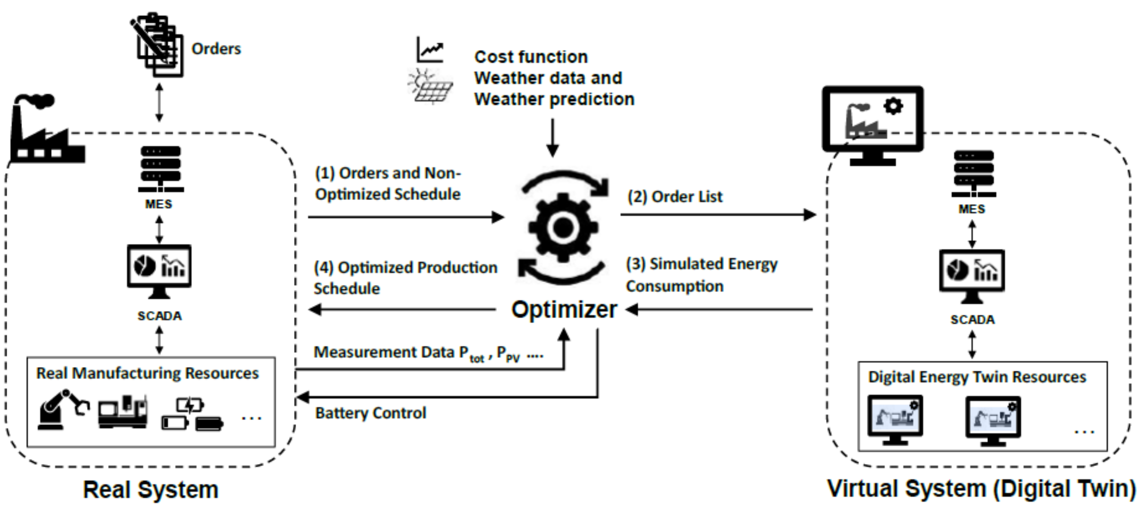


Figure 3: Digital Energy Twin framework of digital factory at FH Vorarlberg.

To simulate the production process, the software ***twin*** from ***digifai*** is used. To this end, a 3D model of the laboratory was created using CAD software, which was imported into the simulation environment, see Figure 4. Corresponding physical properties were assigned to the objects relevant for the production process for enabling interaction between virtual bodies.

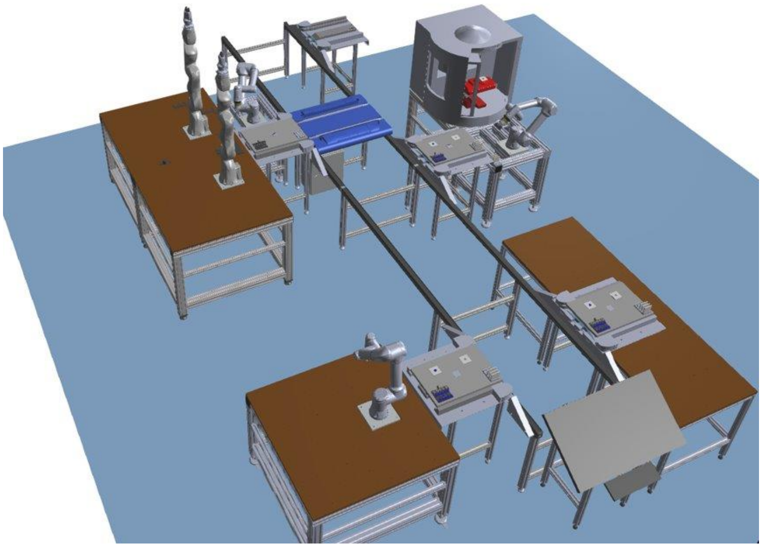


Figure 4: CAD reconstruction of the model factory via the TWIN software by Eberle.

Different technologies are used to simulate the behaviour of existing devices. For the simulation of the UR robots, an offline simulator from universal robots is used. This allows the simulation of the original robot controller within a virtual machine. Thus, programs of the real robot controller can be used directly in the simulation. The communication between UR simulators in the virtual factory is realized by the *RobotControllerConnector* provided by twin. In the absence of an offline simulator for the KUKA iiwa robots, digifai has provided the experimental twin component *GenericRobotController*, which allows generic simulation of a robot with user-defined configurations. Since a direct transfer of the KUKA robot applications is not possible with this setup, the processes were reproduced in twin using *ScriptComponent* modules executing C# code. Also, the essential behaviour of the Transport system and the milling machine were reproduced in C#. In order to be able to control the virtual production on a higher level, a second instance of the real MES and SCADA system was created. The OPC-UA protocol is used for interfacing with the virtual factory. To be able to predict the energy consumption of the production process, the developed energy models were integrated into twin. For this purpose, the neural network energy models (described in the upcoming sections) were converted into functional mockup units (FMU). For this purpose, the neural networks were embedded in a Simulink model, in which also feature extraction and data normalization was performed. The Simulink model was exported as a standalone FMU. The models imported as FMU allow continuous power prediction within the simulation environment.

2.2.3 Use case

The use case investigated has as its main objective to minimize the total energy costs of the system. The cost function considers an electricity tariff for consumed as well as for fed-in energy. Figure 5 shows the possible energy flows in the system including decision variables P_C, P_D and P_G representing power values for battery charging and discharging and electricity consumed from or fed into the grid.

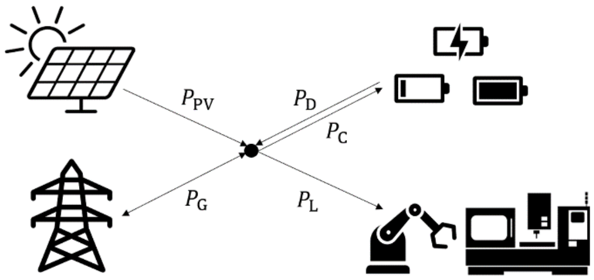


Figure 5: Energy flow diagram of battery-supported factory at FH Vorarlberg

The optimizer uses the digital twin to optimize the energy supply and production schedule of laboratory setup at the FHV. This results in three scenarios: (1) production scheduling to shift the energy demand to the supply (i.e. achieve an optimal load profile of the factory). Notice that restrictions must be considered during rescheduling, e.g. that orders cannot be executed at the same time and that once an order has been started, it cannot be interrupted, (2) battery control to optimally charge and discharge the battery to increase the self-consumption of the PV and to shift the demand to times with lower prices, and (3) production scheduling and battery control combined. Figure 6 shows the system architecture and flow diagram of the laboratory.

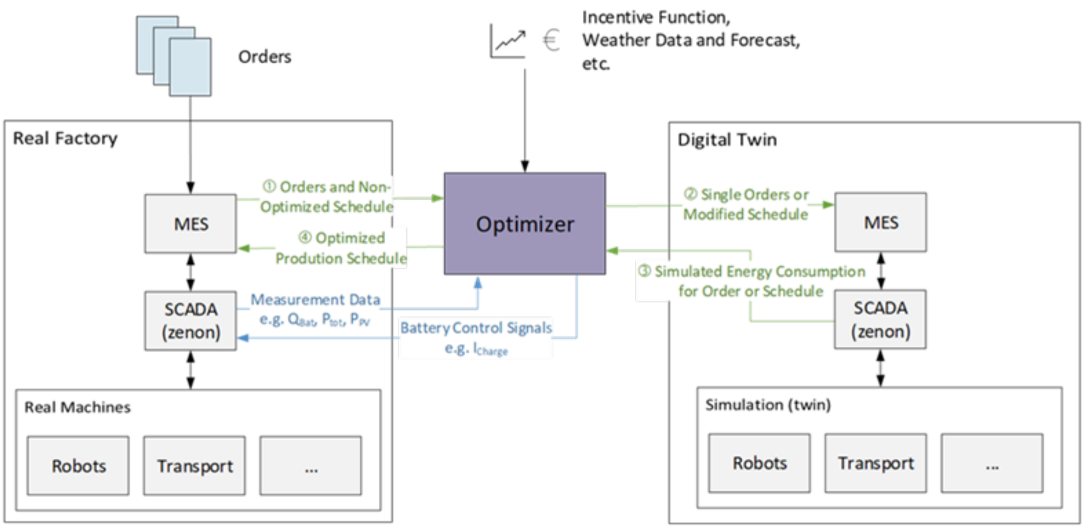


Figure 6: System architecture and flow diagram of the laboratory.

The MES sends the orders and the non-optimized production schedule to the optimizer, which uses the digital twin to estimate the load profiles of the different jobs. Using these load profiles, the weather data and an incentive function, the optimizer derives the production schedule and the battery operation schedule. So, the inputs of the optimizer are a job list, estimated load profiles from the non-linear model of the factory, an incentive function, and weather data (see Figure 7).

The weather is predicted using a Python library called solcast[19] and for the incentive function prices from the local grid operator or the prices from the Austrian energy market (Energy Exchange Austria [20], EXAA) are used. The EXAA energy price is a real-time price (RTP) with a 15 min resolution. Using the energy price as an incentive and the weather as a disturbance, the production schedule and/or the battery control can be optimized. The optimization method is based on mixed integer linear programming (MILP) as MILP assures finding the global minimum and is computationally very efficient. MILP is based on linear programming (LP) and, therefore, it needs linear constraints.

[19] https://solcast.com
[20] https://www.exaa.at

For the battery storage and the energy supply linear physical models can be used. The digital twin of the factory including the industrial robots is based on long short-term memory and convolutional layers and thus is non-linear. Although the model is non-linear, the optimization problem can be formulated linear as MILP. The reason therefore is, that the optimization problem does not need the complete model of the robots as constraints. Instead, our formulated optimization problem only needs the estimated load profiles as constraints and thus it is still linear. To handle uncertainties, a model predictive control (MPC) algorithm is proposed. By continually updating the model and making adjustments based on new predictions and measurements, MPC can optimize control inputs to achieve desired objectives while considering constraints and disturbances in real-time.

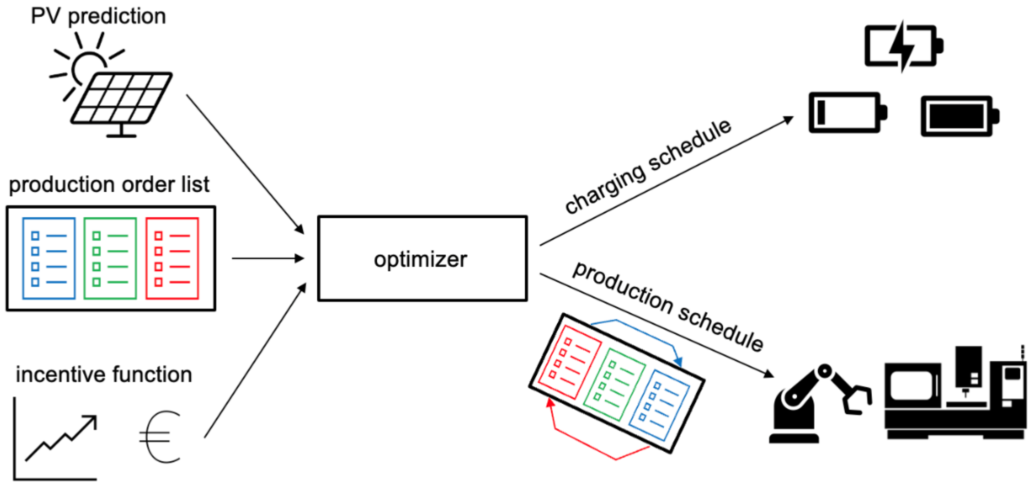


Figure 7: Inputs and outputs of the optimizer.

2.2.4 Modelling

Parts of the system such as PV and battery has been model following a physics-based approach using simplified models. Other parts of the system such as the industrial robots has been modelled following a data-driven approach. The next section focuses on the validation that was performed on developed energy models for the 7-axis robotic system KUKA iiwa LBR8 which is integrated within the digital factory laboratory.

For generation of training testing and validation data, the system was excited with various trajectories whereas electrical power consumption $p(t)$ and the actual position of the axis angles $\theta(t)$ were recorded. To this end, we used two different methods to generate trajectories suitable for excitation, namely:

- Limited space Random – where random positions within a defined subspace of all reachable manipulator poses are generated. The orientation of the end-effector was fixed.
- All Space Random – where random robot configurations, i.e. axis angles, are generated using the entire configuration space of the robot.

Limited Space Random has the advantage that trajectories can be generated more easily and that models, due to reduced complexity, can faster mimic system behaviour. However, such models are likely to not perform well outside the provided training data by extrapolation. To develop model that generalize well over all possible robot movements and to test the limitations of the models obtained by limited space data, the All Space Data was generated as well.

Several trajectories (46 Limited Space, 30 All Space) were created and stored their robot configuration in csv-files, which can be used as inputs for execution on the real robot. To get additional variability and to produce more data out of the same source trajectories, each motion is executed with random blending factor and random velocity. For Limited Space Data 202 recordings corresponding to 2.8 hours recording time were made, for All Space 135 recordings and 2.7 hours. Figure 8 shows an example of one trajectory where also the effect of blending is shown.

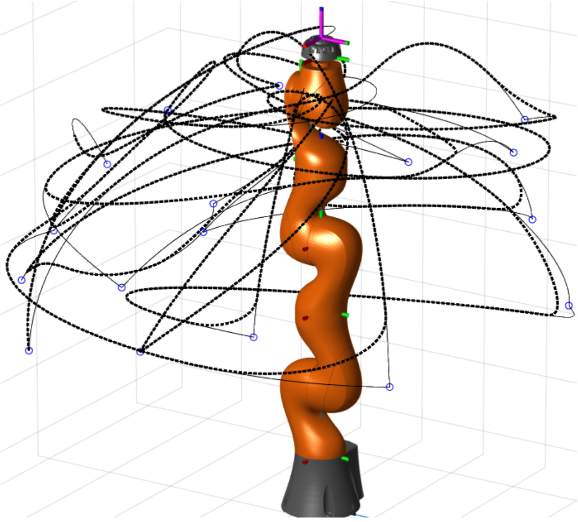


Figure 8: Example of excitation trajectory of All Space Random, points generated trajectory poses are indicated with circles, ptp-motion with blending as fat dotted line.

The setup for obtaining data from electrical and mechanical domains is shown in Figure 9. Power consumption is measured with the measurement box. For the measurement of mechanical data, functions of the KUKA RoboticsAPI are used allowing to save motion data directly on the robot controller as a log-file. The collected electrical data is distributed over MQTT and written to a centra storage (SQL database). The collected data from the database and the controller are afterwards available for further analysis.

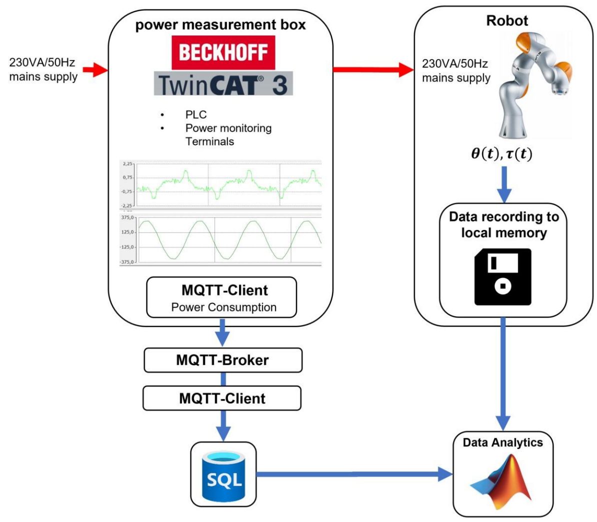


Figure 9: Test measurement setup KUKA iiwa LBR 8.

The used modelling approaches are based on machine learning techniques as well as neural networks and we specifically investigated model structures which can be categorized in:

- Long Short-Term Memory Neural Network (LSTM) with manual feature engineering
- LSTM with Convolutional-Layers for feature extraction

Several variations were trained and tested for each of these structures. The implementation of the models is realized using the MATLAB Deep Learning Toolbox.
The robotic system under consideration was analysed to obtain suitable features for machine learning. We identified the features axis angle θ, angular velocity $\dot{\theta}$ and angular acceleration $\ddot{\theta}$ as suitable. The selection of these features is based on the argumentation, that the consumed electrical power considerably depends on the torque applied on each axis whereas the torque acting on a robot axis can be calculated by solving the inverse dynamics problem, which is given as a set of nonlinear differential equations in the variables θ,$\dot{\theta}$ and $\ddot{\theta}$.
For the generation of LSTM with manual feature extraction, the extraction of the engineered features, the first and second order finite difference method was applied to the recorded data ((1) and (2))

$$\dot{\theta} \approx \frac{\theta(t+\Delta T)-\theta(t-\Delta T)}{2\Delta T} \tag{1}$$

$$\ddot{\theta} \approx \frac{\theta(t+\Delta T)-2\theta(t)+\theta(t-\Delta T)}{(\Delta T)^2} \tag{2}$$

Before the collected data is handed over to the selected modelling algorithms, normalisation was performed.
The chosen base network structure consists of a sequence input layer, followed by a LSTM layer with 10 hidden units, succeeded by a 4 layered feedforward (FF) network without activation functions. The last layer is a one-dimensional output layer. With this base structure, three networks were set up that differ only in their input dimension. The first network has only the normalized seven axis angles as input, the second has additionally the normalized angular velocities as input, which leads to a 14-dimensional input, and the third network has all 21 constructed features as input. The base structure with its variations of input dimensions is shown in Figure 10.

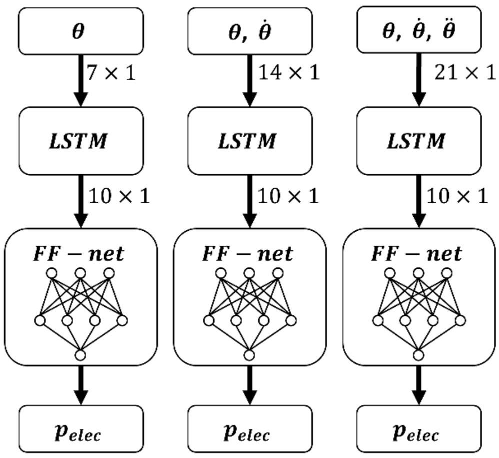


Figure 10: Network structures with manually extracted features of varying input dimensions; from left to right: 7x1dim, 14x1dim, 21x1dim.

In addition to models with manual feature extraction, which require prior knowledge of the system, model structures capable of automatically extracting features from the data have also been studied and developed.
A commonly used layer type for feature extraction in image processing is the convolutional layer, which was also applied for the networks built here. It is interesting to note, that the derivative of a signal can be computed by convolution of the signal with an appropriate filter kernel. Common filter kernels in the field of image processing are thereby the Difference of Gaussian (DoG) for the computation of the first derivative (3) and the Laplacian of Gaussian (LoG) for the second derivative (4).

$$\frac{d}{dt}f(t) \approx DoG * f \tag{3}$$

$$\frac{d^2}{dt^2}f(t) \approx LoG * f \tag{4}$$

The first network structure is a convolution layer with filters of size 1x3. The number of filters is chosen as 2x and 3x. The defined base structure with its variation is shown in Figure 11.

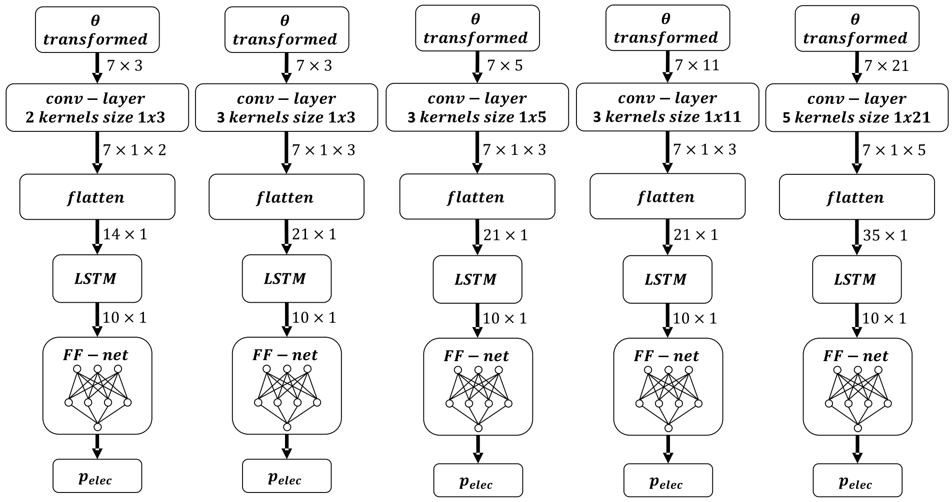


Figure 11: Network structures; from left to right: 2conv1x3, 3conv1x3, 3conv1x5, 3conv1x11, 5conv1x21.

In contrast to the networks with manual feature extraction, the inputs for these networks are only the 7 axis angles. With the number of filters chosen to be 2 and 3, it is intended that the results are comparable to the models with manually extracted features. In addition to the 1x3 networks three further networks were built with a wider receptive field. One with 3x 1x5 kernels, one with 3x 1x11 and one with 5x 1x21.

For model training and evaluation, the collected datasets are split into training, testing and validation datasets. Table 1 shows the used splitting rations. When splitting, we ensured that no recordings based on the same source trajectory were found in the same split. All models were trained using the Adam training algorithm. Table 2 lists the used training parameters.

Table 1: Split training testing and validation data.

	total		training				validation				testing			
	No. Rec.	dur. [min]	No. Rec.	dur. [min]	No. ratio	dur. ratio	No. Rec.	dur. [min]	No. ratio	dur. ratio	No. Rec.	dur. [min]	No. ratio	dur. ratio
Lim. Sp.	202	170	149	126	74%	74%	24	18	12%	11%	29	25	14%	15%
All Sp.	135	162	99	120	73%	74%	18	21	13%	13%	18	21	13%	13%
Lim. + All Sp.	337	332	248	246	74%	74%	42	39	12%	12%	47	46	14%	14%

Table 2: Used training parameters.

	Network Structure	
	14x1dim, 21x1dim, conv-networks	7x1dim
training algorithm	Adam	Adam
max. epochs	2000	2000
mini-batch size	11	11
learn rate schedule	piecewise	piecewise
initial learn rate α	0.02	0.02
learn rate drop factor	0.9	0.9
learn rate drop period	100	100
gradient decay factor β_1	0.9	0.99
square gradient decay factor β_2	0.999	0.9
Epsilon ε	10^{-8}	10^{-8}

Model comparison was performed using metrics *Mean Absolute Error (MAE)* and *Root Mean Squared Error (RMSE)* with focus on MAE.

For better interpretation of these results we show some predictions of the models with input feature dimension 21x1 in Figure 12. The figure shows predicted and measured values in time domain and as a scatter plot. The three plots show the predictions made with the same all space trajectory. The selected trajectory is the one where the model trained with the Lim.+AllSp. data set has the largest MAE.

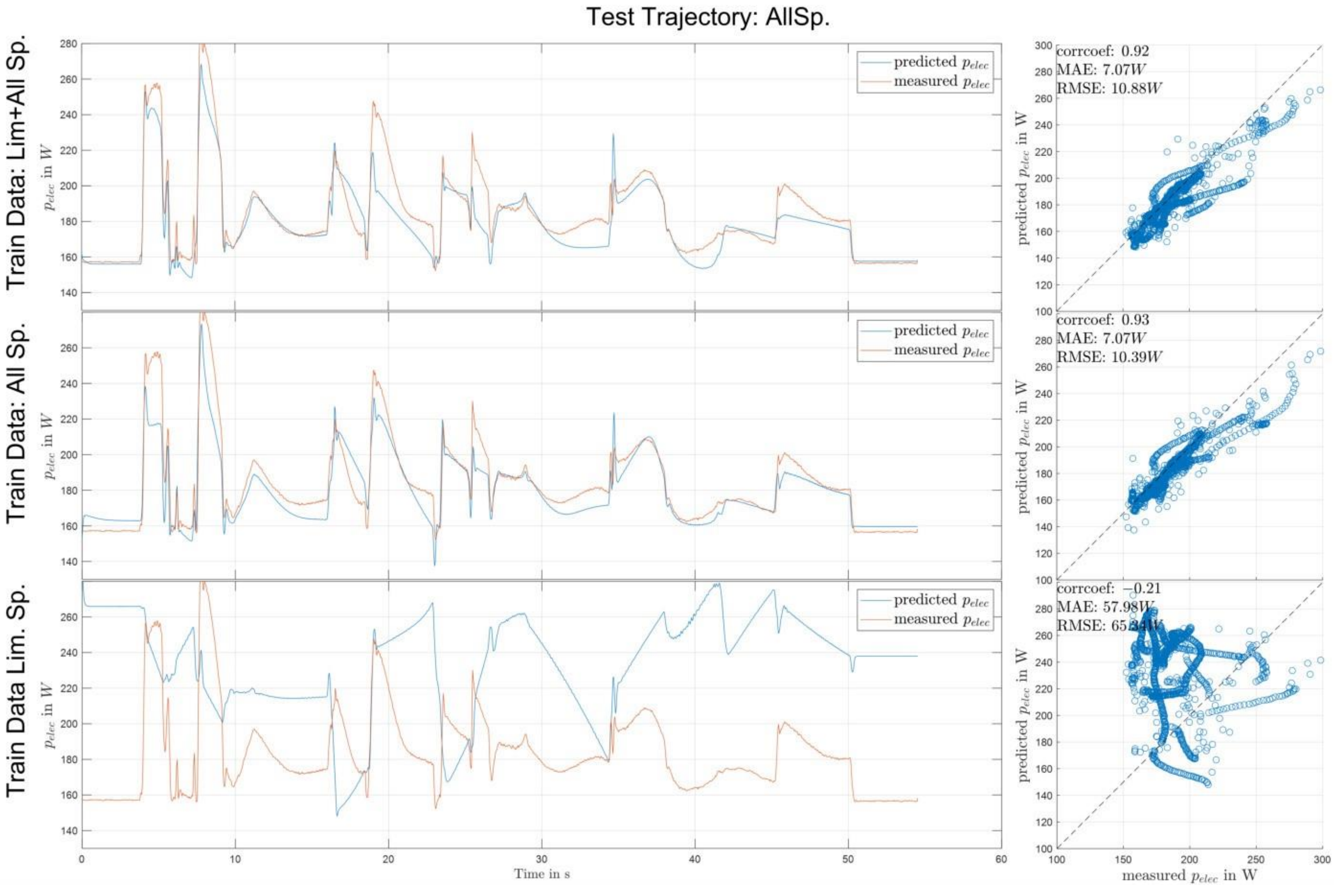


Figure 12: Sample predictions of 21x1dim networks trained on different datasets.

Figure 13 visualizes the absolute errors for the test-dataset as violin plot. A violin plot adds additional information to the structure of boxplots by graphically representing the distribution characteristics of data batches. In the figure, this distribution characteristics are visualized by the symmetric scattering of the data points along the x-dimension. The Figure also indicates median (MED), MAE, and RMSE. The black box indicates the interquartile range. On the right side the complete data (|err| from 0 to 140) is shown, on the left side only an enlarged view focusing on the most relevant aspect is shown.

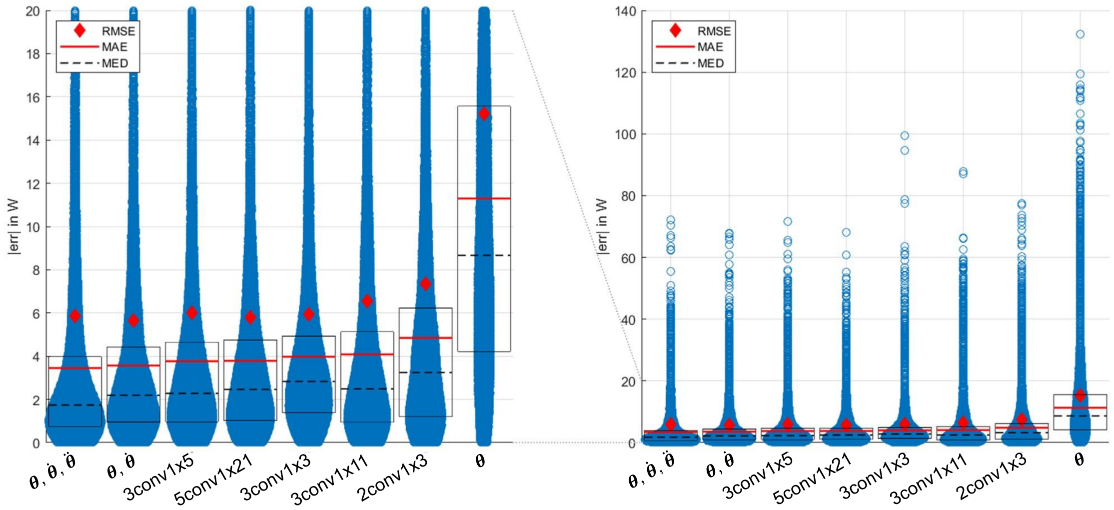


Figure 13: Visualization of |err| for all models.

The performance of the networks with manually extracted features and those with learned convolutional feature extractors are within a narrow range. However, the best overall performance in terms of MAE as well as a narrow interquartile range of absolute errors is shown by the 21x1dim network, which was therefore selected to conduct further experiments.

2.2.5 DET application

The scenarios (1) production scheduling (2) battery control, and (3) production scheduling and battery control are tested using simulations assuming perfect PV prediction. The optimization problem is implemented as MILP is in Python and the Gurobisolver[21] is used. As a reference case, the non-optimized production schedule using battery storage is used. As the incentive function a time of use (TOU) tariff, which is usually a tariff with a price for the day and one for the night, and the RTP tariff from the stock market are compared. A simulation study for one month was conducted. The results are shown in Figure 14.

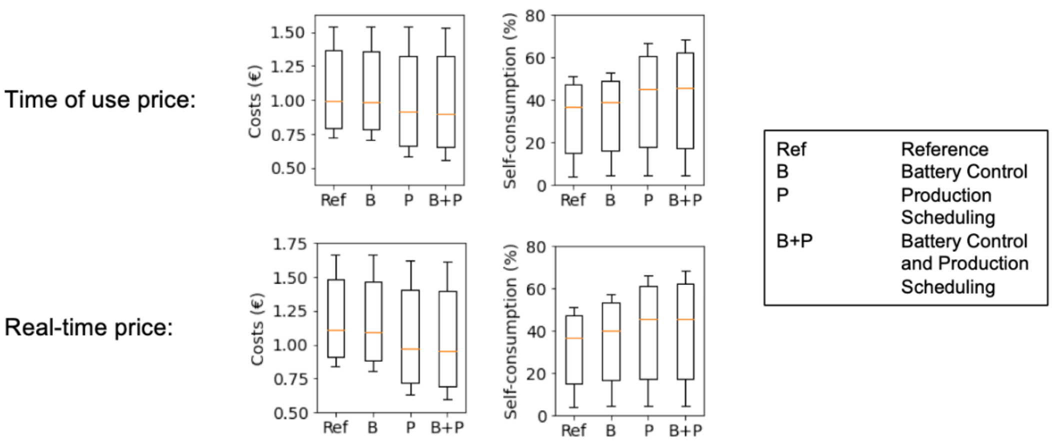


Figure 14: Results of the simulation study over 1 month. Results of the simulation study over 1 month comparing a reference scenario (Ref), battery control (B), production scheduling (P), and battery control and production scheduling (B+P). As

[21] https://www.gurobi.com

incentive function, in the first line, a time-of-use (TOU) price and a peak price tariff from a local grid operator are chosen and in the second line, a real-time-price RTP including a peak price tariff from a local grid operator are chosen.

In simulations, the energy costs for a TOU tariff could be reduced by 8.3% and the energy costs for an RTP tariff could be reduced by 11.9% using battery control and production scheduling. Evaluating the results from scenario (2) shows that only production scheduling reduces the energy costs by 7.2% and 10.9% for the TOU and the RTP tariff, respectively. In contrast, scenario (1) could only reduce the energy costs by about 1% in both simulations. The reason for that is the high costs of the battery including degradation. In the future, higher electricity prices or prices with higher variation could increase this potential. But in simulations, it is shown that production scheduling is the preferred method to reduce energy costs. Although, if uncertainties are taken into account, the battery storage shows its potential. The production schedule cannot be changed in a short time and, therefore, cannot be used in MPC to handle disturbances and uncertainties. In contrast, the battery storage can react fast to changes and thus is able to handle disturbances and uncertainties. In the MPC algorithm proposed, the production schedule and the battery control are optimized at the start of the day. Then, the battery control optimization is run again as soon as new information is available.

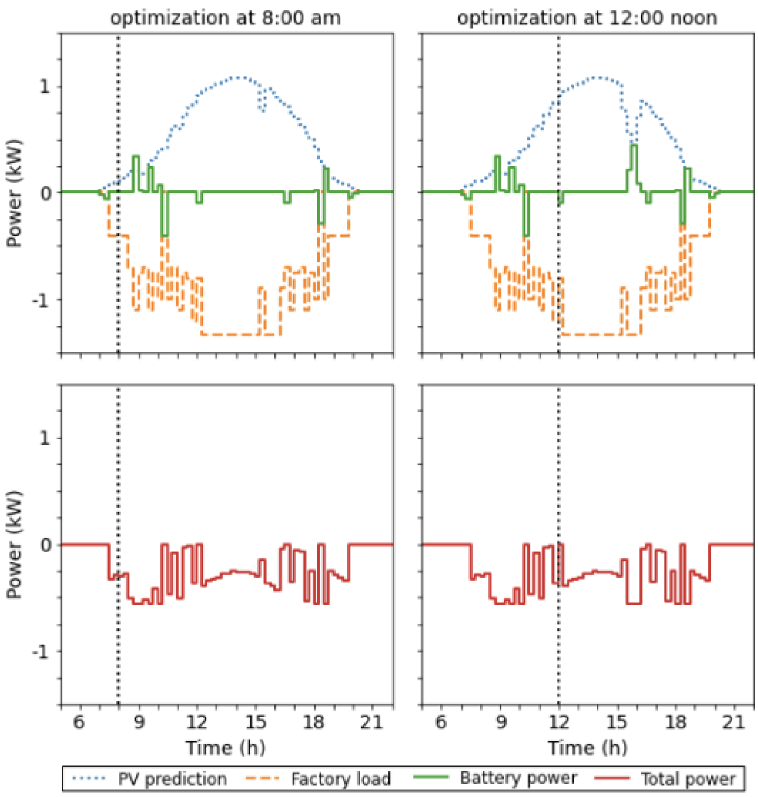


Figure 15 - MPC algorithm handling weather forecast. Example day, where the MPC algorithm is applied to handle uncertainties in the weather forecast. The active sign convention is used, which means that produced energy is positive and consumed energy negative. The total power (bottom) is the sum of the PV power, the factory load, and the battery power (top).

Figure 15 shows the MPC concept for one example day. To show the general concept, artificial data for the weather forecast was used. Initially, only a small PV drop at about 5 pm is predicted. This forecast changes during the day and the battery control has to be adapted to it by compensating the PV drop to not drastically increase the peak power. Using the TOU tariff, the MPC reduced the costs by 7.7 % compared to the initial optimization. This shows how important accurate forecasts or reactions to uncertainties are and that the proposed algorithm can be used for MPC.

The proposed optimization method for production scheduling to increase the self-consumption of the PV was successfully tested in this laboratory. These test runs confirm the simulation results and show the potential of the proposed methods to increase energy efficiency.

More about the above-described method and the simulation results can be retrieved from Wohlgenannt, P. et.al. (2022)[22].

2.3 Use case AT&S

2.3.1 Status Quo

The use case at AT&S differs from the digital factory in that the real system (industrial site) is already in place at the beginning of the project. Prior to the use case definition is therefore necessary to analyse the existing system.
Information about the electricity and gas consumed as well as the heat streams between aggregates (heat pump, boilers, …) and cluster of consumers (e.g. plant 1 high and low temperature, plant 2, …) is gathered to have a first global picture of the industry under study.
Additionally, workshops held between the project partners help identify the most energy intensive industrial processes, namely the drilling process and galvanic bath process for copper plating. At AT&S Hinterberg, drilling process mainly consist of mechanical, laser and x-ray drilling. As the share of mechanical drilling is significantly higher, therefore, it is selected for modelling the drilling process. These two processes were selected not only for being energy intensive processes but also due to their direct influence on the product quality.

2.3.2 Digital shadow framework

The sketched framework and experiences gathered during the setup in Vorarlberg has been used to derive a digital shadow framework for the AT&S case (see Figure 16). Compared to the Digital Energy Twin from the use case at FH Vorarlberg, there is no data flow from the virtual system back to the real system. Data is only transferred from the MES and PDS system in one direction, i.e. towards an external IoT database. The results of any optimization carried out by the DET will not be applied directly to real plant, but rather submitted as a suggestion to a plant operator (decision support tool). This use case demonstrates an operations optimization of the energy supply network at AT&S with high complexity. The main objective is the definition of energy-optimal operation settings of the combined heat and power supply system.

2.3.3 Use cases

The application of a DET at AT&S has been foreseen for design as well as operational optimization. In both scenarios, a comparable approach has been employed to identify various use cases. It mainly consists of data analysis to acquire insights into the system while engaging in discussions with different experts at AT&S and its closely related partners (ENERTEC for the energy system, ATOTECH and Schmoll for industrial processes, bath and drilling, respectively) to define promising use cases.

In regards of the operational optimization, two main use cases have been defined.

[22] Wohlgenannt, M. Preißinger, M. L. Kolhe and P. Kepplinger, "Demand Side Management of a Battery-Supported Manufacturing Process with On-Site Generation," 2022 IEEE 7th International Energy Conference (ENERGYCON), 2022, pp. 1-6, doi: 10.1109/ENERGYCON53164.2022.9830336.).

- **Energy forecasting**. The energy demand forecast models developed for the operational optimization can also be useful by their own stand-alone. Based mainly on historical data several energy-demand forecast models have been developed, some at a high level (e.g. clustered heat demand) and others at machine level (e.g. drilling machine).
- **Operational optimization**. A classical use case which focuses on the definition of optimal operation given an objective function, e.g. minimization of costs and/or minimization of gas utilization. Given several energy demand profiles (heat demand, electricity demand, …) as well as boundary conditions (e.g. electricity costs, …) the optimizer attempts to find out which energy production units (e.g. boilers, chillers, …) should be running and at which load.

Regarding the design optimization, three potential improvements (uses cases) have been identified.

- **Reduction of freshwater consumption**. Fresh water enters the production site and is used in production. The water is being warmed in the process and dumped out of the system afterwards (industry's effluent). The temperature requirements of the process and ambient temperature in the location might allow the regeneration of part of the water via e.g. free cooling, and thus reduced the consumption of fresh water.
- **Supply via return pipeline**. The industrial site has several networks operating at different temperatures. The return pipeline of the high temperature grid exhibits a relatively high temperature (temperature slightly above the requirements of the low temperature grid) so that it could be used to supply the low temperature grid and thus reduce the return temperature and increase the performance of the waste heat recovery units.
- **Industry's effluent as heat source**. Utilizing industrial wastewater as a heat source represents a variation of the first mentioned scenario. In this case, the water leaving the system isn't regenerated via free cooling; instead, the goal is to harness the extracted energy as a heat source for a heat pump. The heat pump is operated when the heat demand is higher than the heat produced by renewable source (waste heat in our case), i.e. use to avoid/delay the use of the gas boilers.

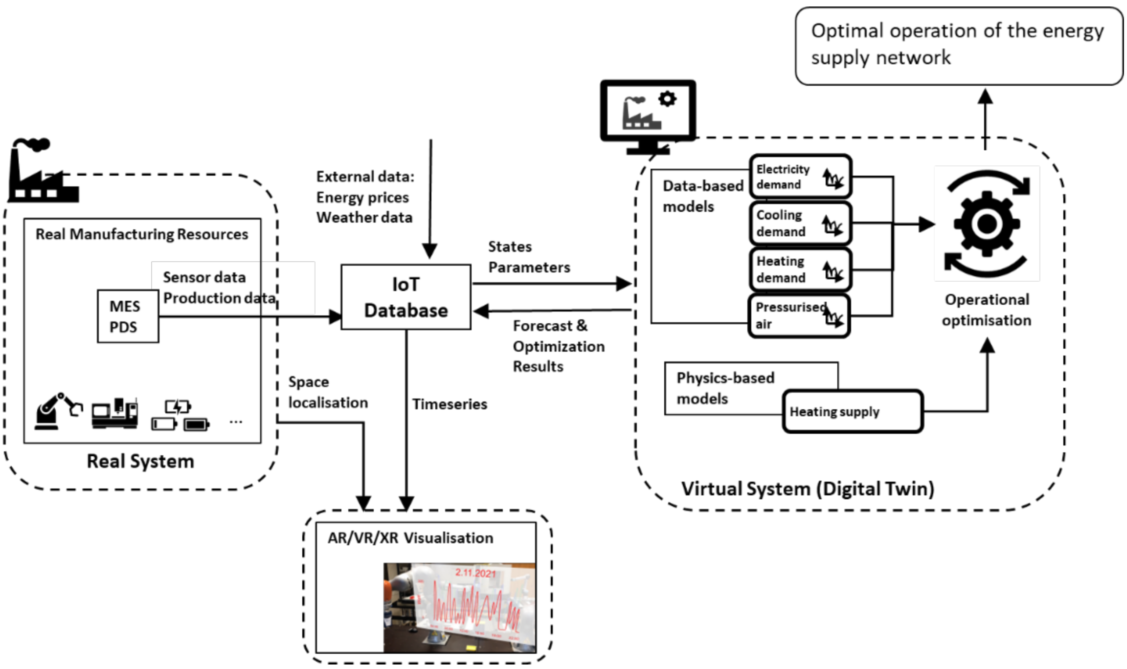


Figure 16: Digital Energy Twin framework at AT&S.

2.3.4 Physics based modelling

As described in the requirements of the DET, two different modelling approaches have been utilized, the physical-based modelling and data-driven modelling approach. The physics-based approach has been used at the AT&S case to model the energy supply units (boiler, chillers, heat pump) as well as the heat recovery system and water tanks. Mainly models of the open-source libraries Modelica Standard Library[23] (MSL) and Buildings[24] were used, e.g. BoilerPolynomial[25] and OpenTank[26] are used to model the gas boilers and water tanks respectively. However, some adaptations were necessary to model the heat pump and chillers which were modelled with the ScrollWaterToWater[27] model. Important aspects to mention to this model are,

- The heat pump model is supplied with functions for the refrigerant R410A. The installed machines at Hinterberg do use R134a instead. Thus, it was necessary to implement a few functions that calculate necessary fluid properties (e.g. enthalpy, isentropic exponent, …). We followed the same approach used by the Modelica Buildings library developers, (methodology described in F. de Monte (2002)[28]) to implement the necessary equations for the commercial refrigerant Freon 134a[29].
- As the name of the model indicates, a "scroll compressor" is considered in the model. The existing heat pumps and chillers at plant 1 (Werk 1) does have screw compressors instead. According to the main author H. Jin. (2002)[30], this should not be a problem since both compressor types are rotatory compressors, quote "The characteristics shared by the twin-screw compressor and scroll compressor make it possible to duplicate most of the thermodynamic analysis for twin-screw compressors for use in the scroll compressor model".

Important to mention is that the parametrization and validation scope was constrained by the available databases, allowing examination only of specific system components, specifically three different chillers and the heat pump.
The parameters used by the model are very specific and are not present in a standard data sheet. Therefore, the model is provided together with a python script to assist on the parametrization. Static operational points are used as a reference, the parameters are iteratively varied to minimize the error between model output and reference values.
The validation is done with measurements at the plant for different periods (between 10 hours until a few days) for different operating conditions (partial load and temperatures). The model results are compared to the reference data, see Figure 17. Unfortunately, the uncertainty and quality of the measurements is significant. Great deviations are observed when carrying out plausibility checks at different parts of the system. Additionally, since not all heat flow rates were measured, we had to deduce the heat flow rate at the evaporator from other measurements (such as electrical consumption and heat flow rate at the source side). Consequently, an energy balance could not be conducted to assess the agreement between measurements. This is a big issue, since deviations on the amount of e.g. chilled water prepared would considerably affect electrical consumption and thus the validation results.

[23] https://github.com/modelica/ModelicaStandardLibrary/releases/tag/v3.2.3
[24] https://github.com/lbl-srg/modelica-buildings/releases/tag/v7.0.0
[25] https://simulationresearch.lbl.gov/modelica/releases/v8.0.0/help/Buildings_Fluid_Boilers.html#Buildings.Fluid.Boilers.BoilerPolynomial
[26] https://doc.modelica.org/Modelica%203.2.3/Resources/helpWSM/Modelica/Modelica.Fluid.Vessels.OpenTank.html
[27] https://build.openmodelica.org/Documentation/Buildings.Fluid.HeatPumps.ScrollWaterToWater.html
[28] F. de Monte. Calculation of thermodynamic properties of R407C and R410A by the Martin-Hou equation of state, part I: theoretical development. International Journal of Refrigeration. (2002) 25. 306-313.
[29] https://www.freon.de/-/media/files/freon/freon-134a-si-thermodynamic-properties.pdf
[30] H. Jin. Parameter estimation-based models of water source heat pumps. PhD Thesis. Oklahoma State University. Stillwater, Oklahoma, USA. (2002)

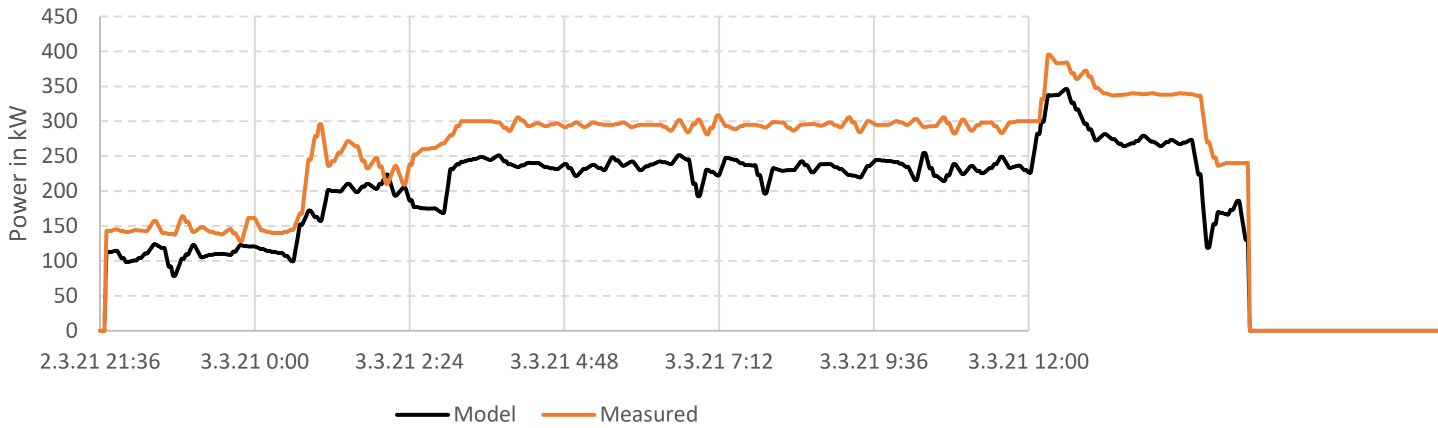


Figure 17: Exemplary validation results period/case 1 for chiller KMA03 with 6 minutes averaged data.

The Mean Absolute Percentage Error (MAPE) is calculated for each period to easily compare parameter sets. Exemplary results are shown in Figure 18. The parameters are iteratively improved until the absolute error is minimized.

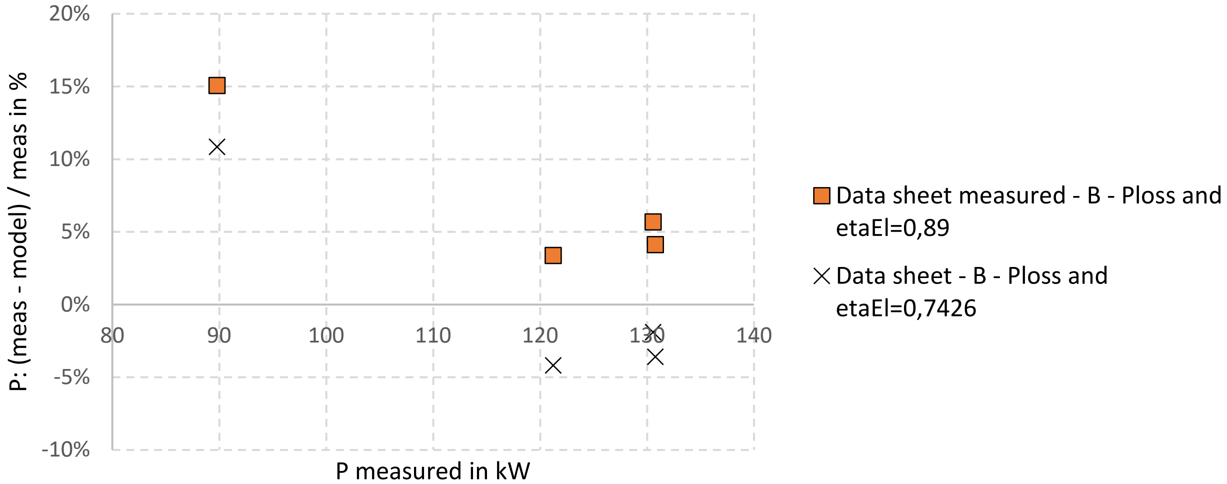


Figure 18: Exemplary validation results period for two different parametrizations considering four different periods/cases for the heat pump.

The error could be minimized for the heat pump model, especially in the full load operation, but higher deviations appear for low load operation, see Figure 18.

On the flip side, the parametrization of the chillers proved to be considerably more challenging, yielding suboptimal results during the validation process. Exemplary results are shown in Figure 19 for the chiller KMA02.

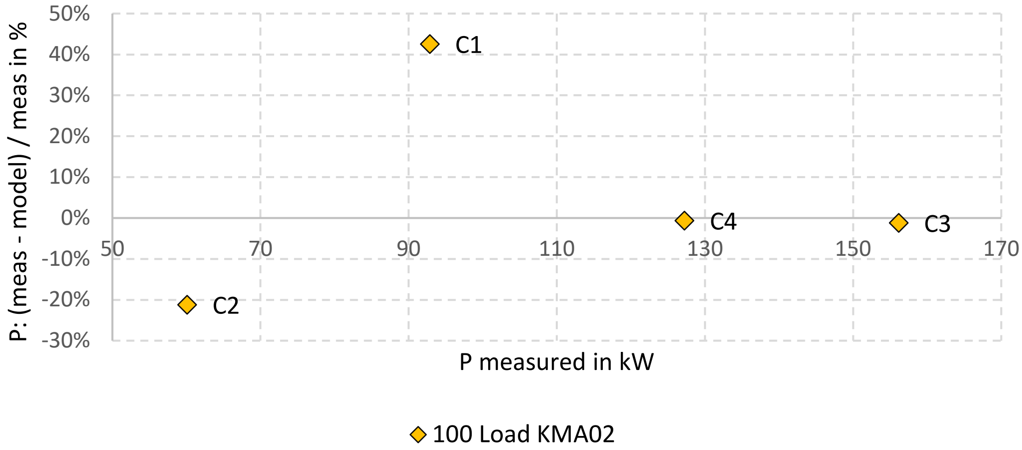


Figure 19: Deviation in % between measured data (data from KMA02) and model output for main parametrizations "F" (based on data at full load operation). Labels indicate case/period.

Notably, significant deviations were observed during low-load operations (absolute error of up to 40%), while comparatively better outcomes were achieved at higher load operations (< 20%). This discrepancy can be attributed to various factors:

- Difference between the model and the real chillers. Unlike the singular compressor in the model, the real chillers have 2 (or 3) compressors. Furthermore, they have the possibility to release heat not only to a dry cooler via the condenser but also to a heat recovery system. This introduces two primary interfaces at the source side, in contrast to the single interface present in the model.
- Increased amount of data needed for the validation. Due to the increased complexity (e.g. two interfaces at the source side; heat recovery and dry coolers, and two to three compresors) increases the amount of data used. Calculating weighted variables is essential to align the data with the model's requirements (number of inputs). This weighting process is aggravated by the low reliability of the data.
- The data quality issue (as already mentioned above). Errors in the measurements yield the model to be tested (validated) for different (deviated) operation conditions than are really occurring and difficult the interpretation of the results.

The system model is mainly set up with help of the main components models described above as well as auxiliary model such as models for pipes, pumps, valves, signals, switchers, from open-source libraries (e.g. MSL and Buildings).

A main based system model is created based on based on plant 1 (Werk 1). It is depicted in Figure 20 and extensively explained in Ribas Tugores, C. et. al [31] together with part of the validation work carried out for the chillers. Based on this main model, different versions can be generated to carry out e.g. design studies, i.e. evaluate different scenarios. The model considers up to five consumer clusters, two heat consumers: a high temperature (HT) and a low temperature (LT) grid. Data of their temperature and energy requirements are available at their main heat exchangers. HT grid supply temperature varies between 80 °C and 50 °C. LT grid supply temperature varies between 40 °C and 20 °C. The cooling demand is divided into two consumers, a main cooling demand with supply

[31] Ribas Tugores, C., et. al. Decarbonization of Industrial Energy Systems: A Case Study of Printed Circuit Board manufacturing. 14th Modelica conference. Linköping, Sweden, (2021). https://doi.org/10.3384/ecp21181497

temperatures between 10 °C and 6.5 °C, and a cooling demand for industrial processes, production in short. The supply temperature for production should not be lower than 11 °C (the supply temperature is set to 12 °C). The fifth main consumer corresponds to the process water. It requires water at a warm temperature level. Exact demands for the industrial process and process water are available as hourly average values.

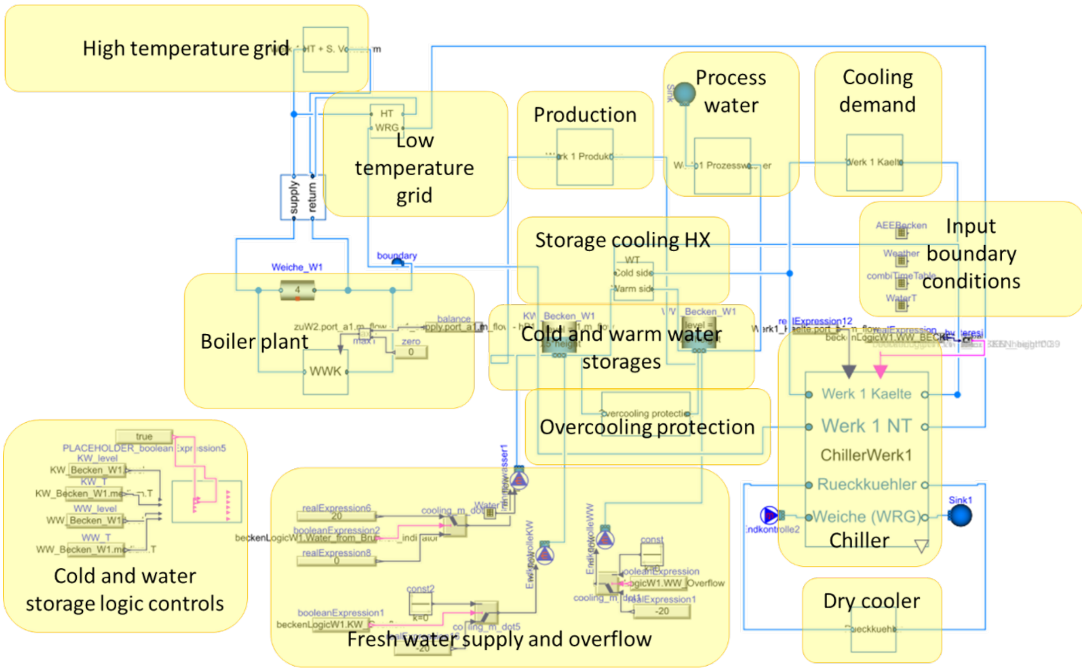


Figure 20: Top level view of the Modelica model of AT&S energy supply system for plant 1 (Werk 1).

This model is then extended to incorporate further existing elements such waste heat from the chillers and compressors into the hydraulic separator (Weiche). Important to mention is that even the model attempts to include all parts of the system and mimic it as good as possible. From a practical point of view is not advisable to include all elements in the modelling and to have a “all-around” model. Instead, the model needs to be adapted to target specific questions, i.e. the model is adjusted to include the necessary parts and level of detail required to solve a specific question. For instance, the focus of the operational optimization is the operation of the chillers. In this regard it is necessary to consider all three chillers per separate (do not cluster them) and consider the cooling and heat demands. The water cycle can be skipped since we do not influence it.
Finally mention that the models obtained to mimic the energy system at AT&S are meant to be used not only for design optimization questions, but also for operational optimization. Since the simulation speed of the model falls short of the required level by the application, the models need to be improved in this regard towards a much faster version. The main approach followed consisted in the generation of surrogate models.

TUG develops a pipeline that is producing a ML-based FMU as a replacement for the physical FMU, including the following steps (see also Figure 21):

1. Generate simulation data based on a physical model (as FMU).
2. Train a ML model using the generated data.
3. Encapsulate the ML model with all needed files in a new FMU.
4. Compare the original physical model with the ML model.

Figure 21: Framework for replacing a physical model with a ML model.

In a first step, a template implementation based on one of the chillers at AT&S was developed. The goal was to develop and test the pipeline with simplified ML models. Figure 22 shows the result of the surrogate ML model (orange) compared to simulated data (blue, labelled as ground truth).

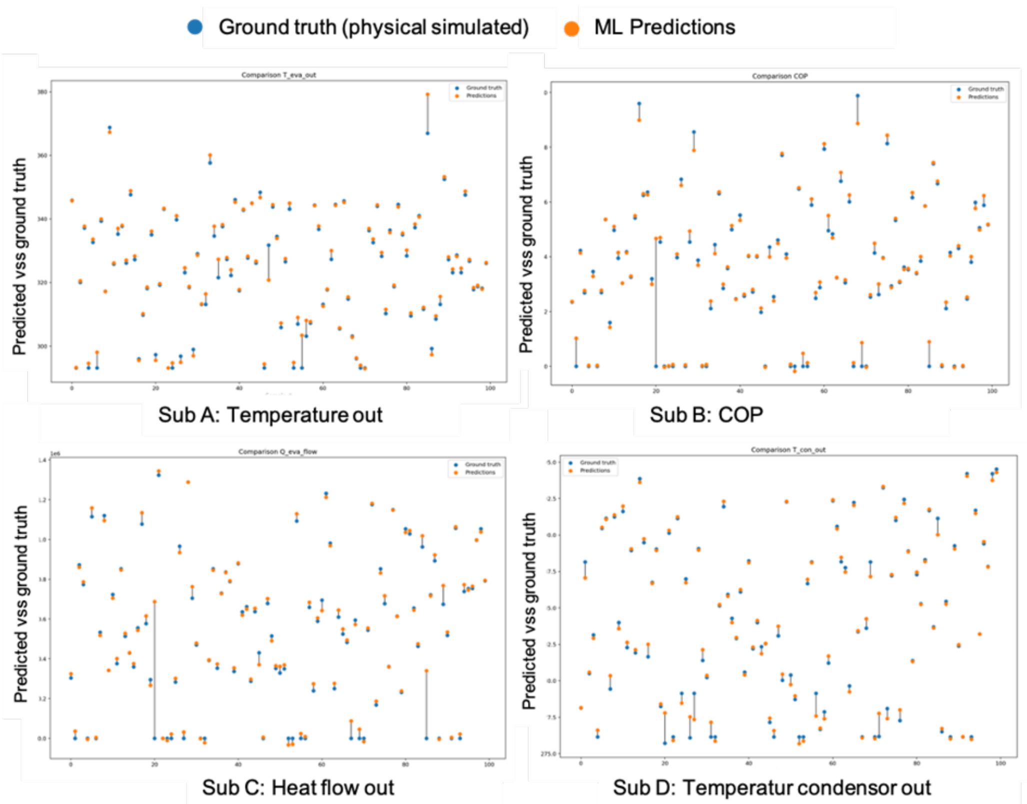


Figure 22: Evaluation of the surrogate ML model based on simulated data.

Similarly, a framework owned by ENEXSA that allows massive parallelization has been further developed to allow the use of FMUs. Specifically, the library PyFMI[32] has been integrated into the framework, see Figure 23.

[32] https://pypi.org/project/PyFMI/

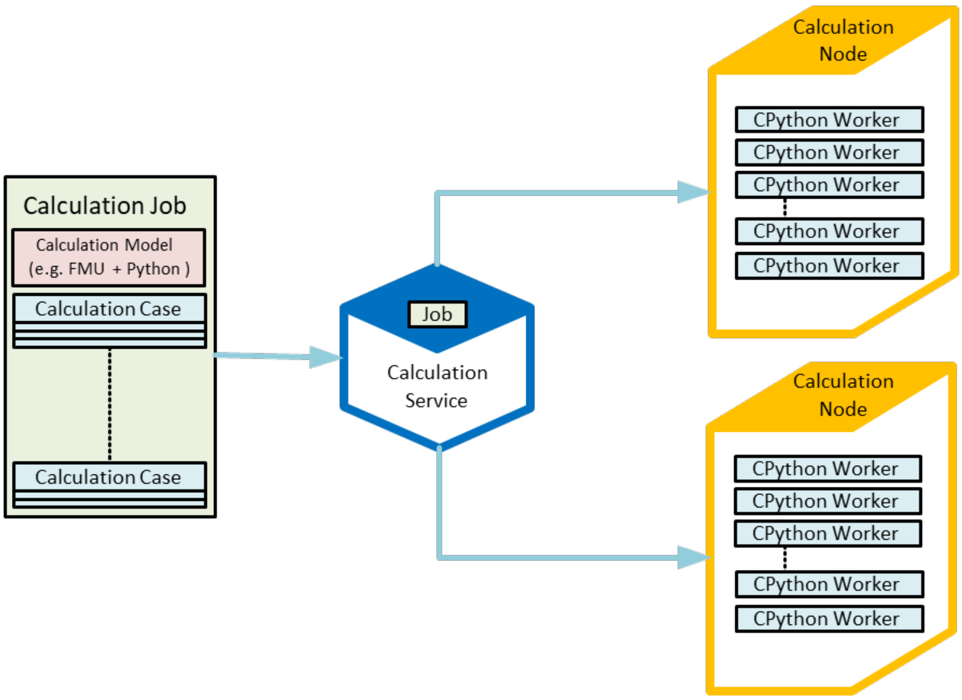
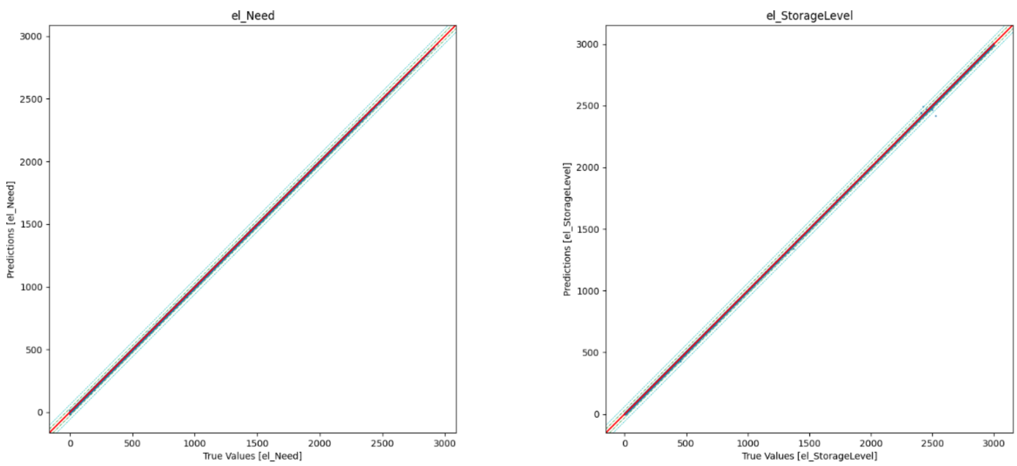


Figure 23: Schema of ENEXSA's extended framework on generation of surrogate models.

This framework has been tested together with MUL. Here a generic energy system model developed in OpenModelica[33] has been exported as FMU and simplified with help of ENEXSA's framework. Specifically, two FMUs have been exported, each with a different charging strategy for thermal energy storage. About 10 million runs (5 million per FMU) have been carried out at a speed of about 1 million runs each 9 minutes (0,086 seconds per run).

The obtained results are utilized to generate a physical-informed neural network (PINN). The surrogate model is compared to the original FMU with satisfactory results, see Figure 24.



[33] https://openmodelica.org/

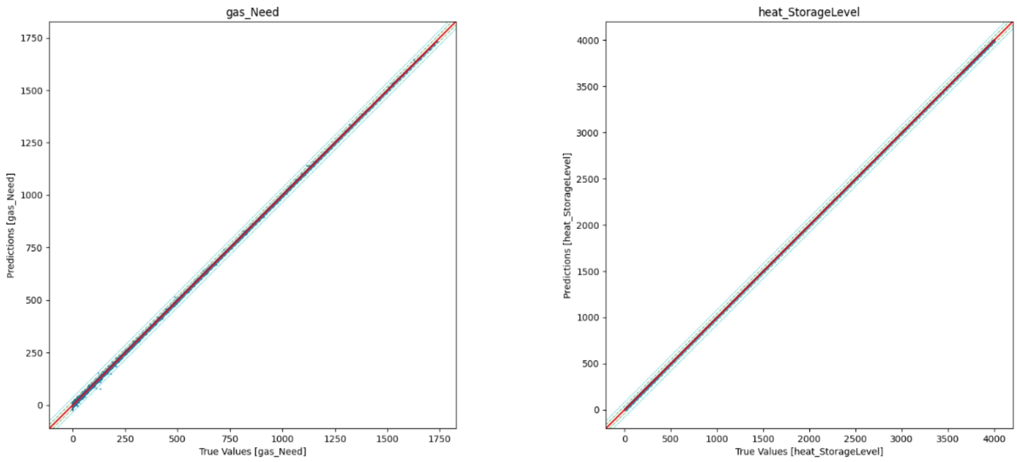


Figure 24: Comparison between reference results (FMU) and surrogate model (PINN) for four different variables: electricity consumption (top left), gas consumption (bottom left) and electrical and heat storage state of charge (right, top and bottom respectively).

2.3.5 Data driven modelling

The data driven modelling approach has been focused on the energy demand of specific machines. The work can be divided into two main parts, a modelling at process level, were the bath and drilling process have been investigated in detail, and a top-level approach where energy demand forecasts have been created at department and/or energy vectors level (e.g. heat demand cluster). The top-level approach was set-up based on a reference model (see Figure 25) used to simulate the energy forecast for later operational optimization procedures. Important to mention is that the data driven modelling work, similarly to the physics-based modelling, face challenges due to limited and sometimes low-quality data.

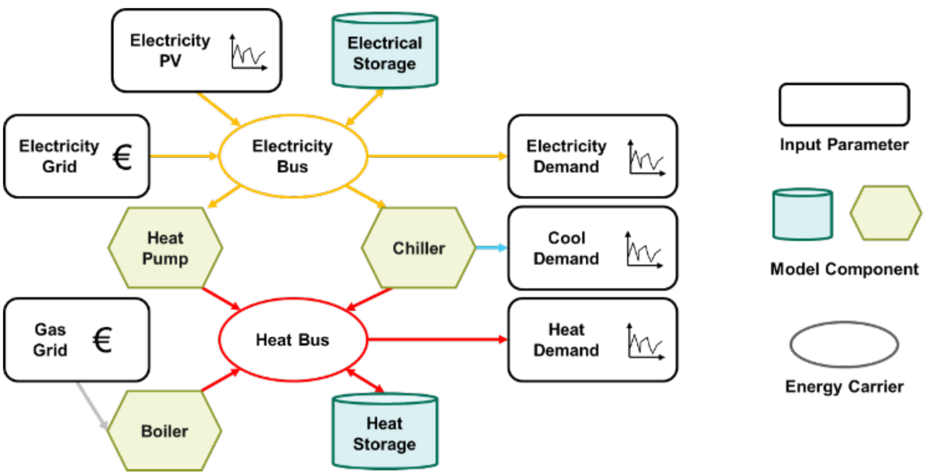


Figure 25: Reference Model for energy demand forecasts and operational optimization

At the process level, a set of laboratory experiments on the drilling process has been carried out by Schmoll and IMPEX to identify critical parameters that influence energy consumption. The discussion of these results it mainly concluded that,

- Variation in energy consumption for different product is negligible,

- energy consumption mainly varies based on the production mode (e.g. standby, dry run or normal operation)
- parameter variation has negligible influence on energy consumption in different production modes (e.g. dry run, …),
- the variation of the parameters has more influence on product quality than on the energy consumption.

Based on the above conclusions of the set of experiments as well as the fact that the parameter selection process for every product is a complex process which is based on expert knowledge and it can hardly be automated, a strategic decision has been made. Our modelling efforts are to be focused on predicting energy consumption rather than on the definition of process parameters. Unfortunately, access to product scheduling data was not feasible during the project. Consequently, the modelling work had to merely rely on historical data of the energy consumption of the drilling department. Results are presented in Figure 27.
The modelling of the bath process has been addressed in two levels, at a small-scale (laboratory level) and with focus on the actual process at AT&S.

Discussion with the bath supplier (ATOTECH) in collaboration with AT&S has been carried out through the whole project. Discussion is aimed to better understand the bath process and the machines itself. These first discussions bring AT&S to provide measurement data of the baths on temperature curves, voltage, and amperage values. The data has been stored into the external IoT database and used to developed function-based models than can predict e.g. temperature based on historical data. Unfortunately, no clear measurements on the electrical consumption of the machines were available at the time. Further discussions with ATOTECH and AT&S regarding the measurements has continued through the whole project, unfortunately data could not be supplied within the time frame of the project so that the further modelling of the bath at AT&S could not followed upon.
On the other hand, bath modelling was carried out at lab-scale at the TU Graz[34]. Main aim was to apply data-driven modelling techniques to predict the copper layer thickness of an electroplating process. Over 200 electroplating experiments took place at the laboratory where main parameters like time, temperature and current density were varied. Different Machine Learning (ML) methods were used and compared, specifically: Neural Networks (NN), Liner Regression (LR), Polynominal Regression (PR), Decision Tree Regression (DTR) and Random Forest Regression (RFR). In general, it was concluded that Polynomial regression performs very well for the Coating thickness prediction as well as the Electric potential energy.
This data model, and even a small polynomial degree has excellent results on the test set and the training set. The other methods also perform well on the data and are very close to the polynomial regression results, especially on the training set, however they have a bigger drop on accuracy for the test set, especially on the prediction of electrical potential energy, see Table 3 and Table 4.

Table 3: Best results for the data models on coating thickness prediction. Source: Digital Energy Twin: A data-driven approach to analyze and optimize industrial energy systems[34].

Data model	R^2 on test set	R^2 on training set
Polynomial regression (degree = 2)	0.982	0.974
Decision tree regression (depth = 7)	0.940	0.997
Random forest regression	0.949	0.994
Neural networks	0.946	0.991

[34] Birngruber, Gerald. Digital Energy Twin: A data-driven approach to analyze and optimize industrial energy systems. Master thesis TU Graz, April 2021.

Table 4: Best results for the data models on electrical potential energy prediction. Source: Digital Energy Twin: A data-driven approach to analyze and optimize industrial energy systems[34].

Data model	R^2 on test set	R^2 on training set
Polynomial regression (degree = 4)	1.000	1.000
Decision tree regression (depth = 9)	0.895	1.000
Random forest regression	0.887	0.987
Neural networks	0.939	0.990

The tested and evaluated methods could not be applied one-to-one to the bath equipment at AT&S due to different reasons. First the complexity of the baths at AT&S is much higher, there are many more variables involved from which e.g. chemical process, no information is available. Second, similarly to the drilling machine, process parameters are very relevant for the product quality, these are defined by experts and cannot be easily modified, so that the method approach would need to re-define the variables used as input. Furthermore, the number of measurements for newly installed baths is much higher, so that a screening and selection of data would still be required.

At a rather top-level, a first modelling attempt has been done by using time series forecasting machine learning model for the prediction of the overall energy consumption. The data was available in a 15 minutes resolution. It trained the model on 11 months of data, where a split the data in 80% training data and 20% testing data was conducted. With the training data, training of different models using various parameters and settings was performed. A comparison between the measured data and the prediction result is given in Figure 26. The model architecture consists of 3 hidden layers with 64 hidden neurons per layer and the ReLU activation function.

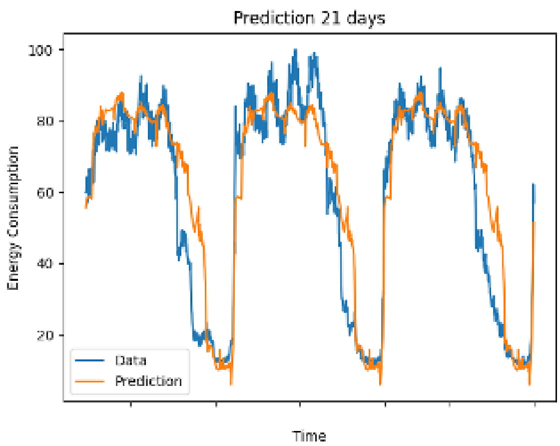


Figure 26: Overall energy consumption prediction.

The forecast was refined by looking at singular consumer clusters. Successful outcomes were achieved for heating and cooling. Notably, accurate heat demand forecasts were generated by considering weather predictions (temperature and humidity). Electricity demand forecasting for the overall demand yielded unsatisfactory results, prompting an individualized examination and Pareto analysis. Simple methods for forecasting were applied to small consumers, while larger consumers utilized more complex methods or additional data. Maintenance intervals proved crucial for some consumers (especially the copper plants). In other areas, such as drilling, information about the production programme is necessary to be able to make a forecast. Here, neural networks, so-called LSTM (long-short-term memory), were used here to be able to carry out a forecast. Exemplary results are shown in Figure 27.

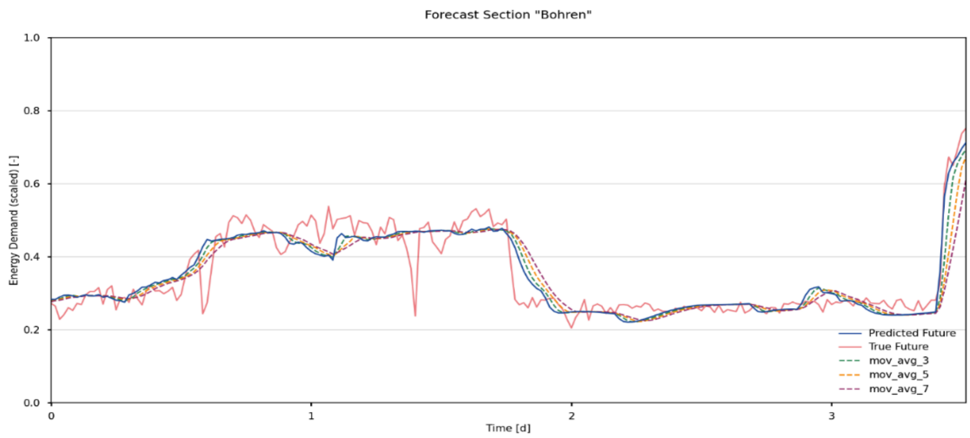


Figure 27: Forecast (blue line) of the energy consumption of the drilling department compared to the measurements (red line).

The models have undergone iterative refinement for improved predictions. Their outputs are intended for independent use by utility operators and can also be combined with a plant model for operational optimization.

2.3.6 DET (digital shadow) application

Offline versions of the models are used for parameter studies, specifically for design optimization. The value lays on tackling the various challenges on the realization of parameter and design studies that do not depend on the data transfer type (offline, semi off-/online, fully automated, …) and need to be dealt with. Key challenges include identifying optimization potential, ensuring model requirements and quality, and addressing data availability issues. Additionally, using a simplified version of the energy system at AT&S, surrogate models and demand forecast models has been used to test the operational optimization framework. This testing involved the application of a genetic optimization algorithm and a subsequent comparison with a linearized version of the models optimized through a mixed-integer linear optimization approach.

The operational optimization work has shown that both approaches, the linearization and use of surrogate models in combination of their respective optimization algorithm, are suitable for simplifying energy systems and their usage in operational optimisation. However, both approaches still have weaknesses that need to be further investigated.

The most significant disadvantages of the linear model are the high effort and the necessary expertise required for its creation and the deviation from the reference model that arises when the capacity costs are considered. Therefore, also a piecewise linearization was used for the optimisation. The results of the piecewise linear optimisation are much better than the results from the original linear optimisation – shown in Figure 28. Also, the computation time for the piecewise linear optimisation is only a few seconds. The establishment of the linear model requires good knowledge of the existing model to be able to derive a linear model from it. For this, the individual components of the energy system must be considered and adapted, which is associated with effort and requires the necessary expertise. This is particularly difficult when models are only available as a black box. To apply linearisation in industrial operations, it is essential to investigate how linearisation can be automated or at least to create a guideline on how to proceed with linearisation. The advantage of the linear model is that a linear optimisation method can be used for operational optimisation. The linear optimisation method guarantees that the global optimum is always found.

In contrast to the linear model, the neural network model has a high degree of accuracy compared to the reference model, see Figure 28. Another speciality is that the results from the reference model tend to be better than those from the neural network when the same input is used. That means, the likelihood is very low that the results from the genetic algorithm getting worse when simulated in reference model. Automation for the neural network development is also easier to implement than for the linear model. Automated model creation would guarantee easier handling in the industry, and the energy system can then be adapted more quickly to changes. Based on this, the neural network model would be preferable to a linear model. The problem with the neural network is that this model cannot be used for linear optimisation. Therefore, a heuristic, e.g. the genetic algorithm, may be used for the optimisation. This has the disadvantage that it does not necessarily finds the global optimum and can deliver different results for the same input parameters due to the heuristic behaviour. If the runtime is long enough, a stable result is achieved. The genetic algorithm needed a little bit longer for the calculation than the linear optimisation but after 1-2 minutes it was also able to reach a stable optimum.

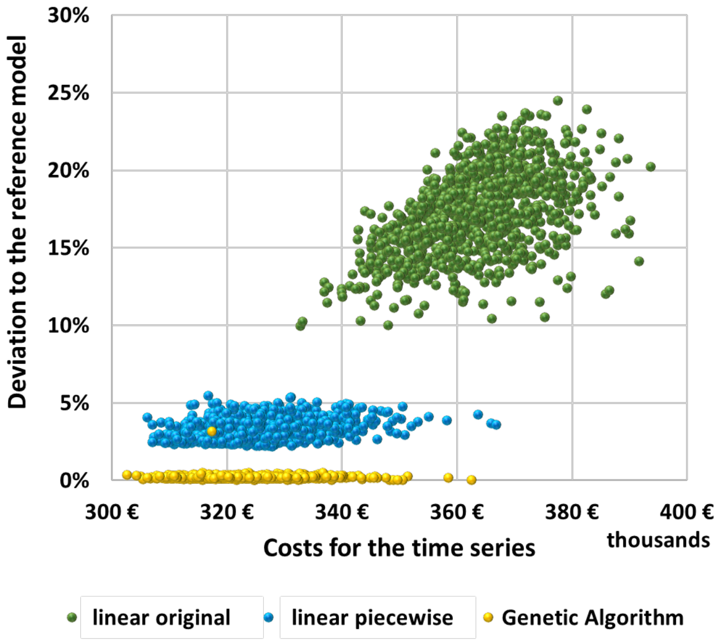


Figure 28: Comparison of the different operational optimization approaches.

In addition, it should be mentioned that a better understanding of the model is possible with the linear model than with the neural network. With the linear model, energy flows between the individual components of the energy system can be considered. In contrast, the neural network only outputs the final results, and intermediate steps cannot be considered. To create the linear model, knowing the individual intermediate steps was essential. From this, it could be determined where the deviations from the reference model originate. The neural network did not show such strong deviations as the linear model. Therefore, a closer inspection of the model is mandatory. The deviation of the neural network was satisfactory and did not need further investigation.

For industrial operation, in addition to the challenges already mentioned, the implementation in a real energy system and the stability of the optimisation results in the presence of changing input parameters must be investigated. Since the input parameters (such as energy demand of production, electricity prices, etc.) are based on forecasts, they can change constantly. The effects of these changes on the optimisation result have yet to be discovered. According to initial assessments, the two optimisation methods investigated are also suitable for more extensive and real energy systems. Another issue with real energy systems is that they can change their design over time. Here, methods still need to be developed on how changes in the energy system desig can be systematically integrated into validated, existing models. If the models can be extended easily, it is possible to simulate future energy systems. Combined with operational optimisation, a wide range of variants for the energy system can be tested, and the optimal design or expansion of the energy system can be determined.

In regard of the design optimization, three cases were studied. These are, 1) reduction of freshwater consumption with help of free cooling, 2) supply of the low temperature grid via return pipeline of the high temperature grid and 3) Use of water dumped out of the system as source for a heat pump.

The first concept consists in instead of pumping fresh water into the cold-water tank, the warm water is cooled down with the ambient temperature and reinjected into the cold water. The analysis on the freshwater consumption pointed out that up to 25 % of the volume dumped out of the system (about 208000 m^3) could be theoretically recovered via free cooling, see Table 5. The theoretical estimation is further narrowed down under consideration of two specific designs, the use of a single dry coolers or the use of two units.

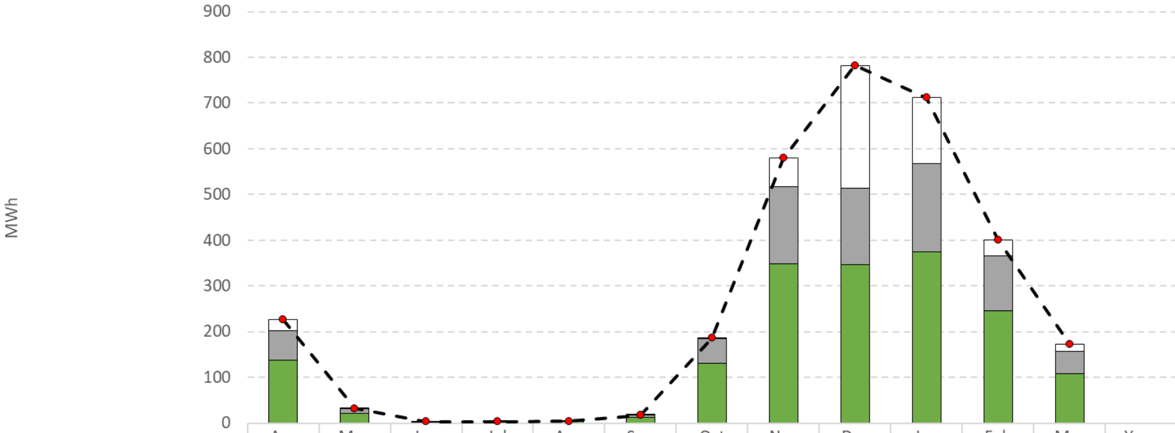
Table 5: Summary results for ideal case and dry-cooler case, with one and two dry coolers.

	Ideal case (10 K)	2 x Dry cooler	1 x Dry cooler
Recovered (m^3)	208.516	207.013	172.883
Recovered (%)	25 %	24,6 %	20,6 %
Electrical consumption (MWh$_{el}$)		9,9	17.6
Efficiency (Wh$_{el}$/m^3)		48	102

The interest and viability of such use case needs further discussions. Firstly, some questions such as whether all water-streams can be regenerated and for how often, i.e. whether quality issues arise, remain unanswered. Secondly, the potential benefit of freshwater reduction has not been fully discussed. 1) The economic benefit due to reduction of fresh water consumption and how this compensate the additional investments due to refurbishment (piping, potentially new dry coolers) as well as 2) more general benefits such as the “freed” capacity that can be potentially used for the upcoming plant at Hinterberg.

Supplying the low-temperature grid via the return pipeline, while an interesting concept, results in a marginal temperature reduction of up to 2,5 °C, with limited impact. However, this study provides an analytical approach applicable to other system parts facing similar situations, potentially under more favourable conditions. Additionally, findings highlight a potential issue with the hydraulic separator, showing higher temperatures at the generation side compared to the demand supply side. The temperature disparity may result from unavoidable mixing and higher mass flow rates at the energy production side. Investigating the necessity of these mass flow rates, with the possibility of localized increments at each unit, could help mitigate the temperature difference.

The third study is a variation of the first one. Here the water dumped out of the system is not “regenerated” but cooled down prior exit of the system. The energy extracted is used as a heat source for a heat pump which main contribution should be used to reduce the gas consumption. The results showed how about 2,5 GWh/a gas could be substituted thanks to the heat pump, from which 1,7 GWh and 0,8 GWh comes from the dumped water (heat source) and heat pump compressors (electricity) respectively, see Figure 29.



	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Year
HP - Sink	202	31	3	3	4	17	185	516	513	567	365	157	2.565
Gas (still to be covered)	24	1	0	0	-	0	1	63	269	144	36	17	554
HP - Electricity	64	9	1	1	1	5	55	169	167	193	120	49	835
HP - Source	138	22	2	2	3	12	130	348	346	375	246	107	1.730
Gas - Status Quo	226	32	3	3	4	17	186	579	782	711	401	173	

Figure 29: Monthly and yearly values of gas consumption of the status quo and potentially substituted by a heat pump using COP Map based on YH13K1E-TFDN.

Checking technical viability is crucial to assess the effort required and adjust the estimated value of the concept. Initial studies may focus on control points E & D, as they offer promising conditions with reasonable temperatures and volume flow rates, providing sufficient heat for a heat pump. Moreover, these streams pass by the "boiler house", offering potential installation space for a heat pump.

2.4 Augmented reality (AR)

The augmented reality technology has been mainly developed in parallel with the use case digital factory at FH Vorarlberg. The here presented methods and use cases are general enough to be applied to other industrial setups (e.g. AT&S).

2.4.1 Requirements

A list of requirements for the AR application has been defined together with potential use cases, i.e. foreseen applications. The energy data related uses cases are,

- the visualization of historical (or predicted) energy data with 2d (or 3d) graphs,
- **data on actual status** of the machine/process. Potential parameters shown are e.g. operation mode, active job name, temperature, etc. see Figure 30.

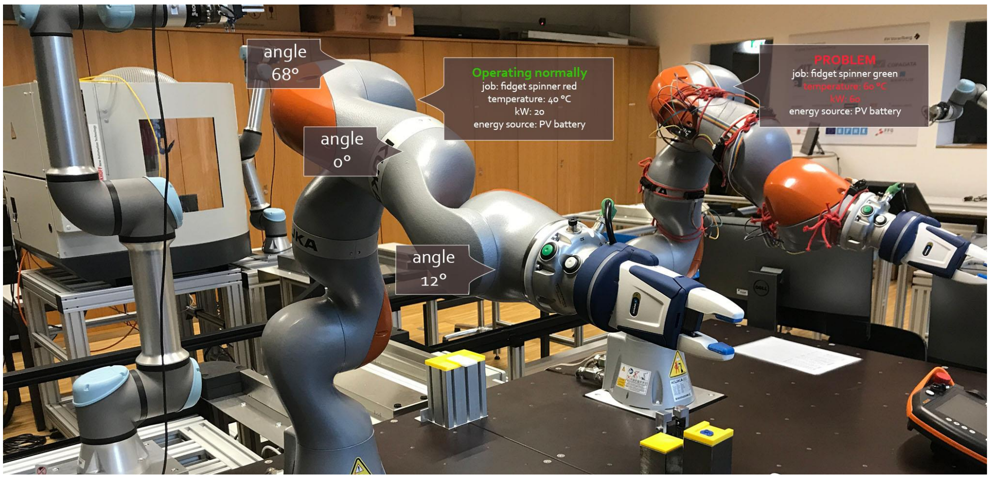


Figure 30: AR status information concept.

Additional cases, with non-energy-related 3d data are,

- **3d model data for production planning**. This allows simulating production lines where specific parts like robots or baths are replaced by or complemented with different equipment. Figure 31 shows how the virtual Servus robot (blue object, orange box on top) looks like in the digital twin software TWIN (digifai) and in the Augmented Reality app from the user's perspective.

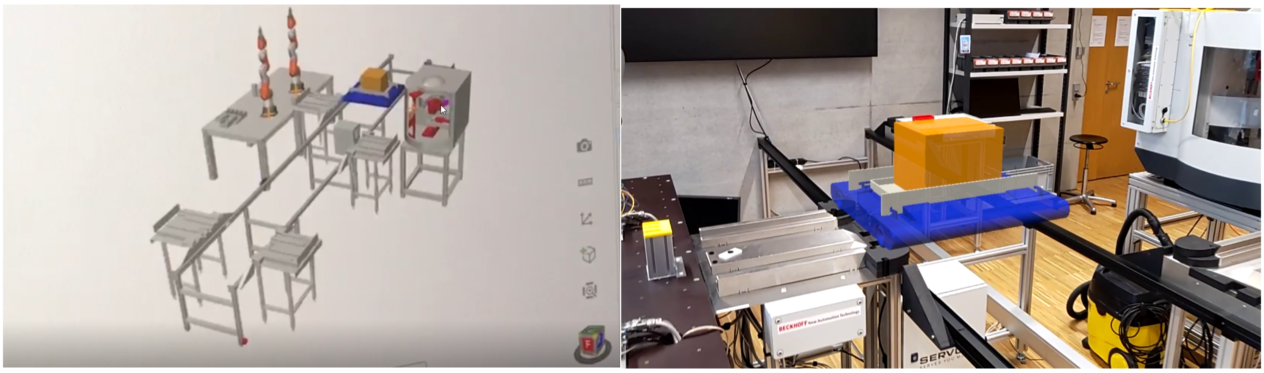


Figure 31: Left: twin simulation, right: virtual Servus robot on empty existing rails.

- **Historical motion data**. Users can see how specific elements of the production line have moved during a chosen period of time in combination with the energy data graph, see Figure 32. Showing the past animation in-sync with the energy data might help identifying issues and correlations between movements during specific production jobs and energy consumption.

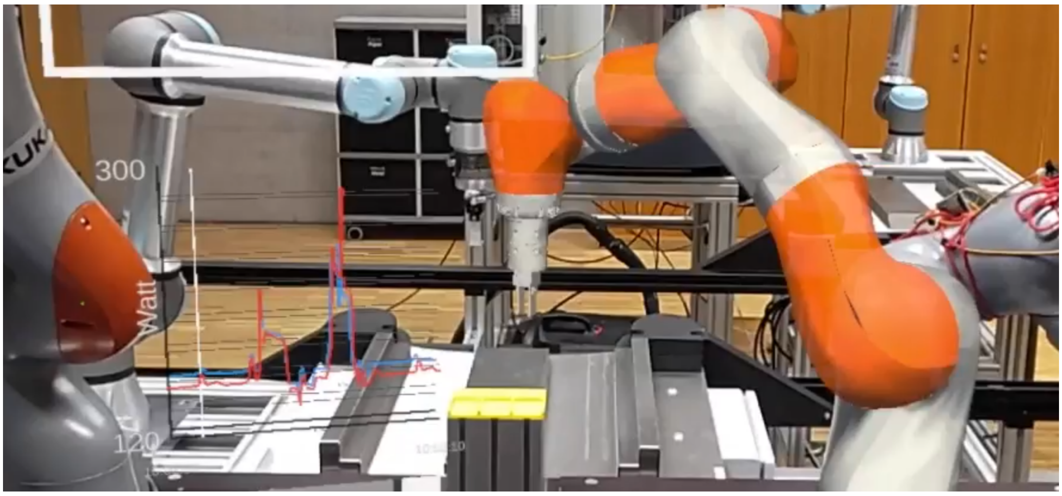


Figure 32: Early visualization of historical energy data (red and blue graph) and correlating robot movement.

Based on the above-described use cases a set of requirements in regard of the needed software and hardware is defined.

Hardware:

- Free movement in the factory (wireless device).
- Accurate tracking of the user‘s position and head orientation.
- Wide Field of View to see large graphs and 3d object in real size.
- High display resolution to identify smaller font text and thin graph lines (FullHD+).
- Precise and robust positioning of 3d objects in larger rooms.
- Intuitive interaction with different elements in 3d space.
- GPU and CPU performance suitable for showing detailed CAD models with a minimum framerate of 20 fps.

Hands-free operation as well as wearing comfort will improve the user experience which eases acceptance. This should be considered as an optional requirement.

Software:

As far as implementing the use case scenarios for an AR device is concerned the following software development aspects have to be considered:

- Performance optimized representation of 3d models.
- Performance optimized data exchange between digital twin software and AR device.
- Two-way wireless communication between AR application and twin software.
- Possibility to access energy and motion data from a database.
- Performance optimized visualization of text-based data (e.g. as graphs).
- Intuitive interaction (e.g., selecting and showing/hiding data).
- Easy adaptation for different use cases and different production lines.

Based on the requirements listed, a Plus-Minus analysis (PMA) on the key equipment AR-glasses has been carried out. The Microsoft HoloLens 2 has been chosen despite its limited field of view due to major positive points such as hand and eye tracking, high quality waveguide displays, precise 6 DOF tracking, sophisticated SDK with good support and all of it with a reasonable performance.

2.4.2 Framework

The framework has been iteratively developed throughout the whole project. A key aspect is that the application considers two possible main states (modes), real-time data and historic data (it includes predicted and recorded data), for which the requirements differ greatly from one another.

Real-time data

In the real-time state, the application will handle 3D model data from the Twin software and represent / build them in the HoloLens application. Therefore, a constant connection to the Twin server is required. The HoloLens 2 and the computer that the twin software is running on need to be in the same wi-fi.

The architecture of the Twin connection is shown in Figure 33. The ApplicationManager's Start method serves as the application entry point, with the Update method running each frame, ideally at 60 times per second. The VisualisingController is responsible for visualising both the twin's 3D model data and machine data (additional information about parameters or states regarding the twin). It uses DataProviders for fetching the data and a PositionProvider for determining the position, the scale, and the rotation for placing these data correctly in physical space. ModelData objects contain the information that is needed for displaying 3D models. They hold MeshData objects with Triangles, Vertices, and Normals and a TransformationMatrix with the position, rotation, and scale of the model. MachineData objects contain the information associated with one related machine data set, including its position within the 3D model.

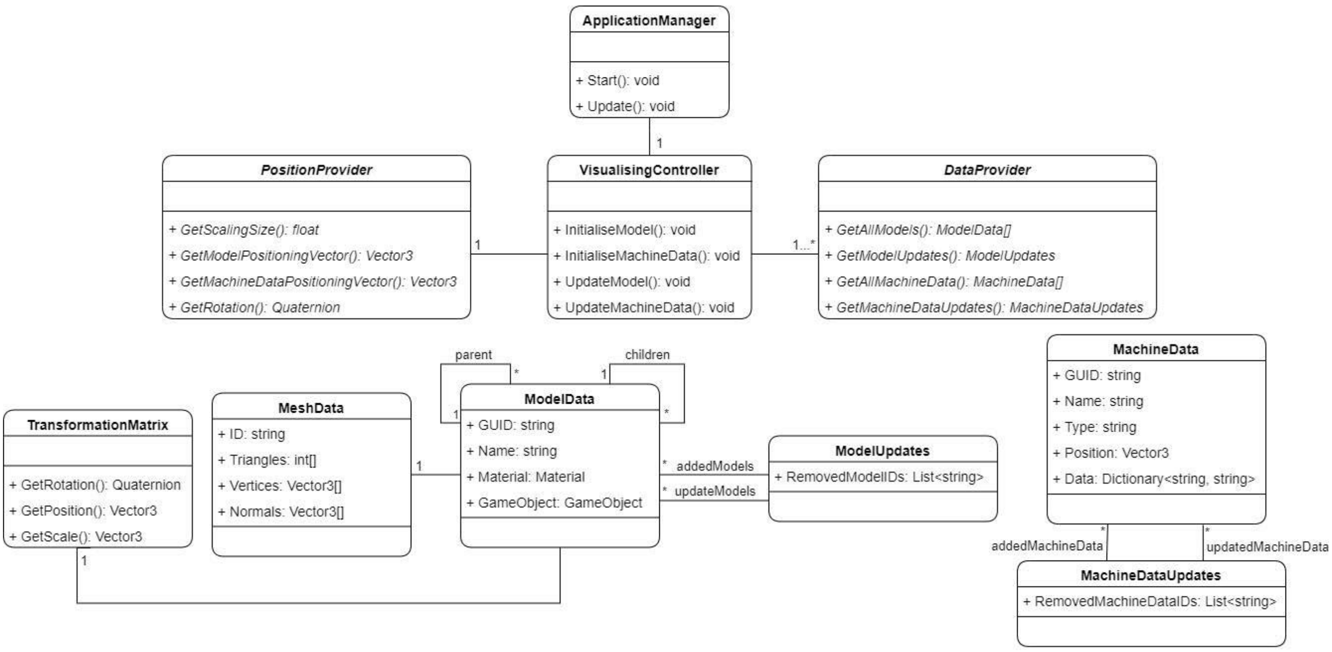


Figure 33: Architecture for the Twin connection.

Historic data

A Model-View-Controller (MVC) architecture is used to represent the data. As shown in Figure 34, there is one group that takes care of the main graph systems. This group consists of the Graph2DController and the Graph2DLineView and -InformationView. The Controller handles the logic while the Views take care of representing and visualising everything. The Model of this MVC system is the CSV_GraphReader (could later be adapted to support other data formats than CSV). This class reads the data and arranges them in a useful way for the Controllers. Another group is the Range group which consists of an IntRangeVariable and a RangeSlider. This class is responsible for letting the viewer select a range of the graph so that they may zoom in or out of the graph. The last group is responsible for animating the production unit according to the recorded data. In the beginning this will be a Kuka robot that's why the elements are named accordingly – however, in the end the type of unit doesn't matter and a robot or machine at AT&S can also be integrated without any additional effort.

The arrows show the dependencies, meaning that for example the KukaAnimationView is dependent on the KukaAnimationController. Notice that nothing is dependent on the Kuka Animation group, which allows graphs to be made without any Kuka animations. There are also nowhere any circular dependencies.

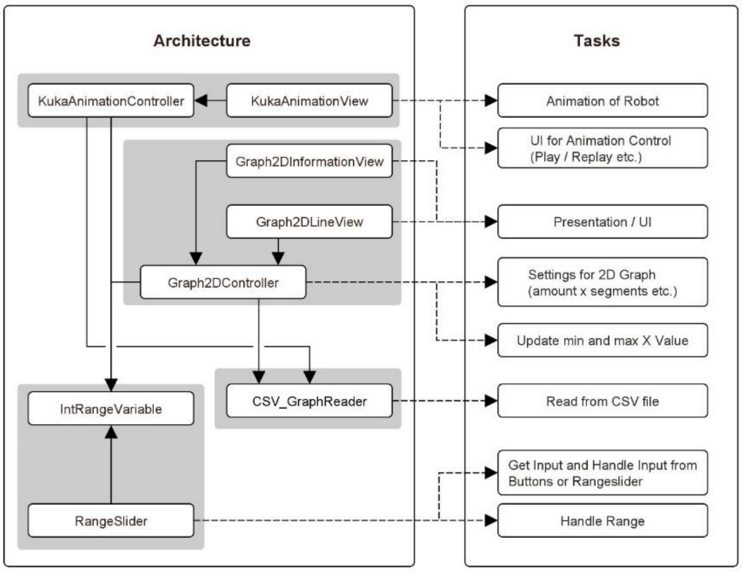


Figure 34: Graph Architecture.

As far as the communication between the digital twin software TWIN (digifai)[35] and the HoloLens is concerned, different protocols were tested, especially JSON[36] and protobuf[37]. The first one is used due to better readability and therefore handling and interpretation of simple contextual data such as descriptions, device values, etc. However, as far as performance is concerned, protobuf is superior and the right approach for transferring more time-consuming and -relevant data types (Krebs, B., 2017[38]). Therefore, all 3d models of the digital twin are transferred via protobuf to the HoloLens.

2.4.3 Application

The final version of the Digital Energy Twin app consists of the following 3 main parts, based on real-time (using digifai TWIN software) or historical machine data (importing database entries as CSV files):

1. an interactable terrain graph that shows watt consumption, time and multiple job curves. Pins can be used to mark specific locations on this terrain graph to easily compare multiple scenarios.
2. a 3D robot arm model that acts as a copy to the real-world robot arm and animates according to the graph data.
3. power cables that are generated between multiple points and indicate where the energy from each job is coming from.

[35] https://www.digifai.com/en/twin/
[36] https://www.json.org/json-en.html
[37] https://protobuf.dev/
[38] Krebs, B. (2017). *Beating JSON performance with Protobuf.* Auth0 - Blog. https://auth0.com/blog/beating-json-performance-with-protobuf/ (accessed 17.12.2021)

Further information not related to energy data was kept to a minimum, as user tests showed that too much information could quickly become confusing. Also, some of the ideas from earlier concepts were seen unnecessary, for example showing the rotation angle of the robot-arms as text, because it is much more intuitive to just see the actual 3D-model animation.

To simplify the usage of the application, the robot arm and all other 3D-objects use the same method of placement: users can simply grab, rotate and scale everything to exactly fit their needs.

The graph-view that is used to visualize current and historical data went through many iterations as well, ranging from more traditional 2d-graphs floating mid-air to more 3-dimensional graphs that use different kinds of interactions to navigate. The final version uses the best of both worlds: easy to read 2d-graphs that are arrayed in a terrain-like structure. This immersive data visualization enables a fast and visual comparison of energy levels, without switching through menus or using filters.

The final graph visualization seen in Figure 35 looks very much like a terrain model, where the length (x-axis) is the time, the width/depth (z-axis) are different job curves, and the height (y-axis) is the watt consumption. This visualizes all the information at once, without having to switch views or choose different curves. It also makes the task of finding energy spikes or valleys very easy and intuitive. To mark those spikes, a pin system was implemented that works very similar to pins on a corkboard. If you place a pin on the terrain, it will display the watt value at that given point in time for the selected production job.

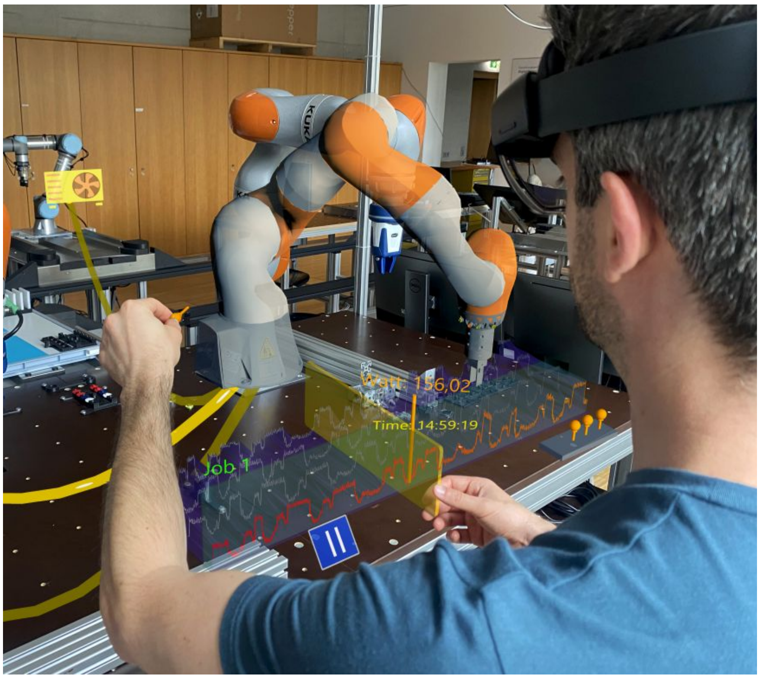


Figure 35: Final version of the energy twin application.

If a user wants to select and display a specific time they can do so by grabbing and moving a plane through the terrain model. Along the other axis is a second plane, that is used to select one of the jobs. All of these interactions use limits and snapping to prevent interactions that would yield unintended results or be confusing, like moving the plane outside of the terrain or vertically rotating the terrain.

Figure 36 shows yellow cables used to visualize where the energy is derived from. At the end of each cable is a small icon, indicating the origin (sun, battery or heat pump). If a cable is active the texture will start scrolling and make it look like energy is flowing into the robot arm. The cables are procedurally generated, so that they maintain a correct start and end point, even if they get moved during runtime.

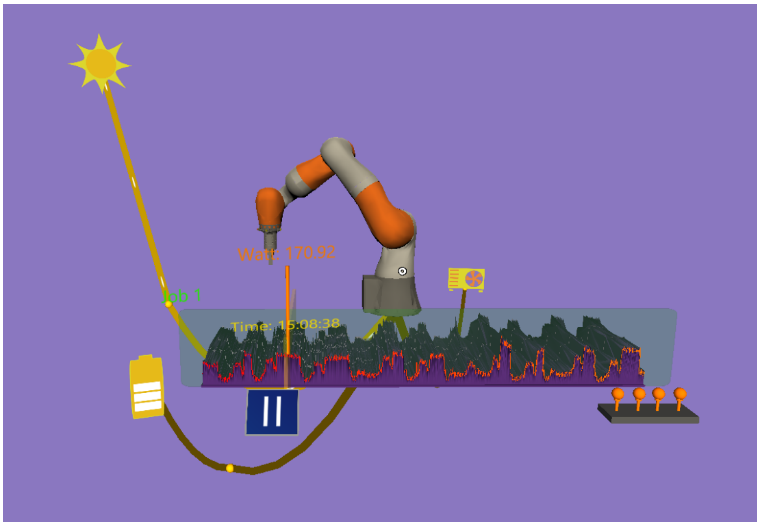


Figure 36: Screenshot of the application inside the unity editor.

2.5 Virtual reality (VR)

2.5.1 Requirements

Similarly to the AR case, the requirements of the VR application were defined based on potential use cases. The use cases are divided in two categories, connected to the digital twin and only representing the digital twin). These specific use cases are:

Only representing the digital twin category:

- **Evaluation and user studies**. E.g. assess how different users (expert, novice) interact with different processes or machines in different scenarios under a safe environment.
- **Educational and training purposes**. VR as a safer, cheaper, and more accessible way to train and educate personnel on work related tasks and/or unfeasible situations (e.g. emergency situations).
- **Understanding and decision-making**. VR environments can be used to help decision-makers to understand better current situations and constraints. It can also be used to show the current development to e.g. the general public (e.g. virtual company tour) to understand better the developments and machineries.

Representing and connected to the digital twin category:

- **Remote operation** of digital twins.
- **Remote Collaboration and Guidance** to have a more direct communication and overcome the limitations of traditional digital collaboration tools that create a division of “person space” (verbal and nonverbal cues) and of the “task space” (space where they work together). This division often leads to misunderstandings, errors, and delays.

Hardware:

- VR HMD with a high display resolution (to read texts)

- User-friendly and intuitive controls and interactions
- High performance (rendering of large models)
- Easy to setup

Software:
For implementing the virtual environment, the following requirements should be considered:

- Intuitive locomotion in a large room
- Performance optimization when rendering and interacting with large models
- Data exchange interface
- Intuitive interaction with the in-world objects
- Flexibility and adaption of the environment and use cases
- Feedback based on the interactions (for training purpose)

Based on the requirements listed, a Plus-Minus analysis (PMA) on the key equipment VR Head-Mounted-Displays (HMDs) and software has been carried out. The main requirements here are usability and flexibility. As a results, the evaluation is limited to four devices, see Table 6. In regards of software choice, a first prototype for a VR application was done with the Unreal engine. However, based on the outcomes of the AR application, an implementation of the prototype in Unity was also carried out.

Table 6. VR Hardware pros and cons.

Device	Pros	Cons
HTC Vive Pro	_high frame rate _user-friendly controllers	_external PC necessary _cables _costly with 1.400€
Oculus Rift S	_ergonomic controllers _lightweight _fast set up _cost-effective with 400€	_external PC necessary _cables
Oculus Quest 2, Pro	_standalone mobile headset (can be connected to a PC) _lack of wires and mobile _cost-effective with 350€	_not so powerful _cables for connection might be necessary _Facebook account necessary
Valve Index	_high frame rate _wider field of view _controller technology	_external PC necessary _cables _costly with 1.000€

2.5.2 Framework

The functionality of the VR application can be categorized into two main modules: visualization and training. In both cases some main interactions for object manipulation (e.g. grab, touch) and user movement have been defined and implemented. These are,

- **Object Grab**. There are two kinds of grabbable objects in the environment: free grab and dedicated area grab interactions (see Figure 37). The free grab interaction can be used for the objects whose grab location is not critical. The dedicated grab area can be used for objects where a specific location or area on the object should only grab by a specific hand. As an example, there can be a sphere that the user can grab from any location but there could be a box that the user can grab only in the handle location. In this application, we will use the trigger button or grip button/pressure based on the VR device for grab interaction.

Figure 37: Left: free grab interaction, Right: dedicated area grab interaction.

- **Touch and hand over interaction**. In this case, the user's virtual hand should work as a physical collider for the touch-interactable objects. In order to make the interaction simpler, we lerp between default hand pose to the touch-interaction hand pose, i.e. pointing pose, based on the distance to the interaction position. In addition, there can be interaction with objects only by hovering over them. This kind of interactions will use the overlapping area of the hand to trigger the functionality.
- To enhance the user experience and simplify interaction, we smoothly transition between the default hand pose and the touch-interaction hand pose, such as a pointing gesture. This transition is determined by the distance to the interaction position (as demonstrated in Figure 38).

Figure 38: Change in the virtual hand pose based on the distance to the touch-interactable objects.

- **Locomotion systems**. There are three main locomotion systems in VR environments: 1- Physical movement 2- Continuous movement 3- Teleportation (see Figure 39). Physical movement is the most natural and easy-to-use type of locomotion system with the least amount of cybersickness. However, it will be limited by the physical boundary of the user’s play area in the real world. The continuous movement can remove the limitation of the real-world environment, but it can lead to high level of cybersickness. Teleportation can reduce the problem of cybersickness; however, it will cause disorientation issues. We considered all three options for the user to give them ability to freely choose between all three options.

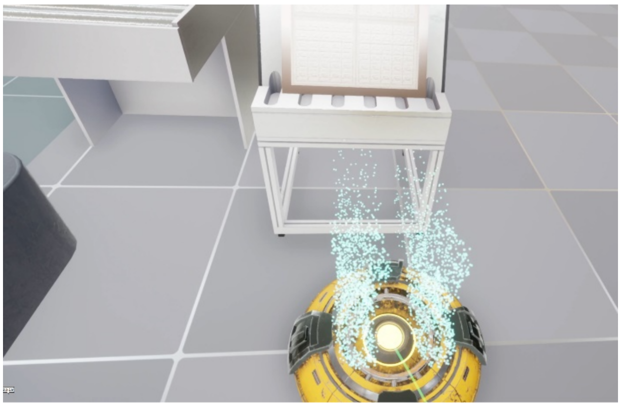


Figure 39: Teleportation will happen by indicating the teleport location.

Though several potential applications have been defined to obtain a set of requirements for the hardware and software, for the implementation of the framework two main use cases, “VR for training purposes” and “VR for data visualization”, have been chosen.

In regard of the VR for training purposes, this application requires a set of pre-defined tasks that the user should complete in order. In each tutorial scene, there is a task manager that is responsible for activating the current task and deactivating the previous task (already done). In order to get track of all available tasks in the scene, the task manager contains a dictionary of task objects in the scene and the execution order of them. Accordingly, level designers can easily change the execution order of tasks in order to change the training scenario. Each task object has a task description and optionally extra information. These descriptions will be visualized as text in the scene with different text formatting styles. In this way, the level designer can inform the user about the current task and the required steps to fulfil it. In addition, there is a list of designated hints for a particular task. These hints can help the user to recognize the current progress of the task.

2.5.3 Application

According to the described concept for the VR application, we developed a VR environment to support the predefined goals for training and data visualization purposes.

VR user interactions application

We defined a set of tasks based on the input by AT&S regarding the training module for one of the stages in the PCB panel production line. Users in this environment will learn about some critical steps and consideration when they encounter this stage of the workflow. The task description is visualized with a text component that shows task id, task description and additional information regarding the task. The following steps are implemented in the current version of the application.

- Grab and placement of the PCB panel (see Figure 40).
- Using the vacuum button to fix the PCB panel position on the device.
- Using the robber roller to clean the PCB panel.
- Push the PCB panel into the device to start scanning the panel.
    - Aling the scan image of the PCB panel with the predefined pattern.

Figure 40: The structure of training module in the beginning stage.

The internal evaluation as well as the evaluation with AT&S of the application has served to improve the application. Besides some minor interaction and bug fixes related to the physics and touch interactions, the following main aspects were addressed,

- Addition of feedback on accidental touch of the PCB panel.
- Add additional rules (e.g. number of times) for the cleaning step of the PCB panel to adjust to the real requirements.
- Avoid finger free gloves as VR hands.
- Add reset option for the training scenario.

VR data visualitzation application

In the data visualization module of the application, we implemented sample devices from production line of the PCB panel to visualize the pre-recorded energy consumption data on each device. The data is illustrated using point plots, see Figure 41. Users can touch each point on the graph to emphasis the data on that specific point on the graphs, see Figure 42. The data can be inserted into the graphs using csv files. Developers have access to several parameters related to each graph such as visualization elements, color, and symbols to customize the graphs. In addition, using several handles, users can change parameters of the graphs in the runtime.

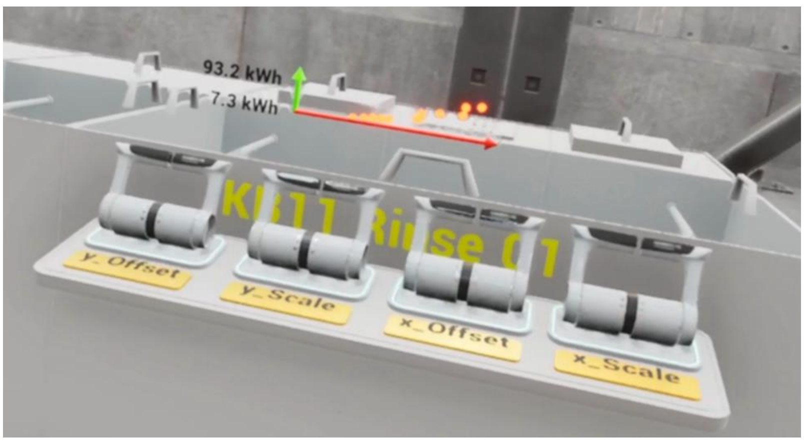


Figure 41: Graph visualization module on a part of production line.

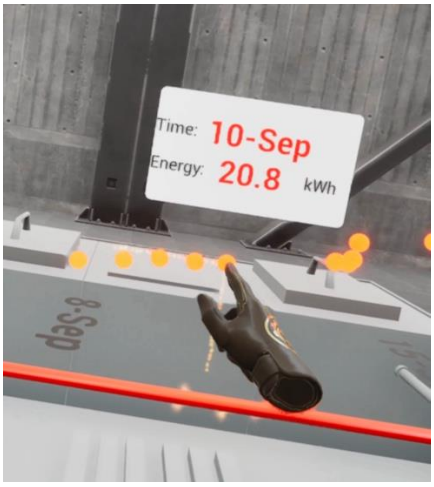


Figure 42: Hand interaction with point on the graph to get additional information on that point.

3 Results and Conclusion

The digital energy twin at the digital factory demonstrates the potential of the digital twin's methodology for industries with help of use cases on operational optimization. Specifically, simulation results show that energy costs can be reduced by implementing battery control and production scheduling, with an 8.3% reduction for a time-of-use (TOU) tariff and 11.9% for a real-time price (RTP) tariff. Production scheduling alone reduces energy costs by 7.2% (TOU) and 10.9% (RTP). On the other hand, the digital shadow created for AT&S demonstrates the potential use for design optimization, several measures were evaluated indicating potential for a 25 % reduction of freshwater consumption via free cooling and a reduction of gas consumption of more than 2 GWh/a by integrating a heat pump and making use of the industrial effluents.

There is quite some flexibility on how a digital energy twin can be build. From the experiences gathered through the project, the following is concluded.

- **The use of industrial standard is key** not only for the modelling of the system with the use of FMUs but also at machine level with use of well stablished communication protocols (OPC-UA, Modbus, …).
- **Physics-based and data-driven modelling** both are suitable for DET applications. Each with its own advantages, drawbacks, and limitations, the choose between approaches can be done individually. Important to mention, is that as demonstrated in the project, some of the drawbacks can be overcome, e.g. slow physics-based models can be substituted by (faster) surrogate models, and e.g. limited amount of measured data to generate data-driven models can be extended with additional dedicated lab-runs.
- **The availability and quality of the data is critic** for the modelling of the real system, for the parametrization/training of the models as well as their validation.
- The use of a **cloud data base**, as provided by Eberle with its Control platform, is a central part of a DET and an enabler for all tasks involved in the implementation of a DET.

Furthermore, the applications created for augmented and virtual reality (AR & VR) proves the maturity of hardware and software solutions available in the market and showcase new possibilities on how to interact and work with digital twins as well as a set of potential new use cases that can be tailored to any industry such as education/training and enhanced graphical representation.

4 Outlook and recommendations

The project “Digital Energy Twin” resulted in two different use cases on TRL4 and TRL5, showcasing the possibilities and problems of Digital Twins in real production environments on lab scale and in productive industrial environment. The following aspects have been identified as the most important issues for the development of Digital Energy Twins:

- Importance of data availability and quality for modelling tasks (parametrization/tunning and validation).
- There is “hidden” potential for optimization energy efficiency in industry. Data analysis as a key step to find potential measures.
- Cloud Database as central part of the digital energy twin
- Benefit of standard FMU proven (Relatively straightforward extension of ENEXSA and Eberle software framework to include FMUs thanks to open source)
- Challenge to link model parameters to product quality and energy consumption for complex industrial processes → Production schedule and operation mode might be enough for forecasting energy demand accurately, i.e. no need to overcomplicate modelling work.
- The requirements for a DET implementation are strongly related to data availability and quality

For industrial implementations, the interdisciplinary cross play of various stakeholders is very important to develop Digital Energy Twin solutions. The partners within the Digital Energy Twin consortium altogether generated specific knowledge to create and integrate Digital Energy Twin solutions. This unique capability is summarized in the form of business model canvas, presented in Figure 43. The main value proposition of the Digital Energy Twin is the optimisation of the energy supply (electricity and heat) for production processes. It also includes a decision support tool for production scheduling. All required key activities (data consulting, data management, modelling, system integration and visualization) can be provided by the DET consortium partners. The targeted customers are medium and large-sized companies in the production industry with electricity, heat, and compressed air demand. As the product is highly customised, the customer relationship is a cooperative stakeholder relationship.
The cost structure of such a business includes mainly human resources, fees for software licenses and databases, and IT hardware. Revenue is generated from data services, data consulting, model creation, license sales, training and service contracts.

The Digital Energy Twin project formed a group of experts able to develop and integrate a Digital Energy Twin for industrial applications. The characteristics and problems identified during the project can be considered and handled by the Digital Energy Twin consortium partners, leading to a perfect foundation for future services and developments in that field. Application partners are encouraged to contact the Digital Energy Twin project team to receive assistance for Digital Energy Twin developments.

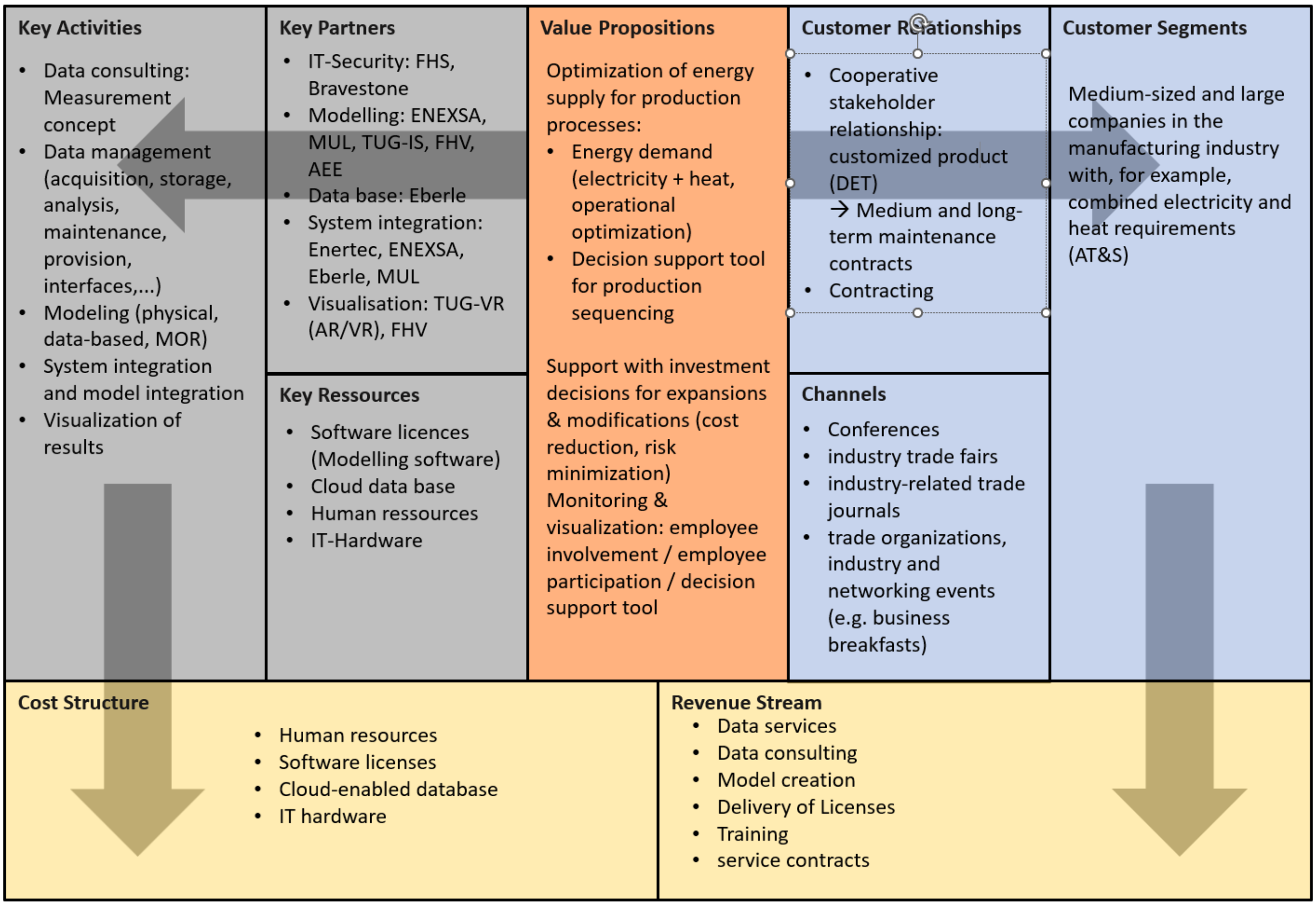


Figure 43: Business Model for the Digital Energy Twin consortium.

5 Related Literature

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Christoph Brunner, Jürgen fluch	AEE	Fachzeitschrift	Digital energy twin Intelligente Steurung industrieller energierelevanter Prozesse	June 2020	https://www.klimafonds.gv.at/wp-content/uploads/sites/16/MI_2020_v8b_EN.pdf
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