ISEC 2024 – 3rd International Sustainable Energy Conference
Solutions for Climate Neutral Industrial Production
https://doi.org/10.52825/isec.v1i.1089

Published: 26 Apr. 2024

IT-Framework for Digital Energy Twin/Shadow Applications

Wolfgang Weiß[1], and Carles Ribas-Tugores[1]

[1] AEE INTEC, Austria

*Correspondence: wo.weiss@aee.at

Abstract. Digital Energy Twins are IT systems, interconnecting sensor data, simulation models and user interfaces to formulate a virtual representation of the behavior of real energy systems. Digital Energy Twins are useful to predict the behavior of energy systems under varying boundary conditions and to optimize their operation considering economic and ecologic impact. Two different concepts of Digital Twins applicable to industrial energy systems were demonstrated: Digital Energy Twins and Digital Energy Shadows. While in literature, the term "Digital Twin" is widely used as synonym, for rather different applications involving simulations and virtual models connected to real-world data, this paper elaborates on the differences between digital twins and digital shadows in more detail. Given by the complexity of real-world energy systems (heat and electricity) and their implications on real time simulation, the concepts are demonstrated on different TRL levels. The results show the benefits and limitations of Digital Energy Twin and Digital Energy Shadow applications in relevant environments.

Keywords: Digitalization, Digital Twin, Energy Efficiency, Design Optimization, Operational Optimization

1. Introduction

According to [1], the degree of data integration is used to characterize Digital Twins. A Digital Twin hereby consists of physical objects and digital objects, exchanging data either automatically or manually. If the data exchange between the physical and the virtual object in both directions is manual, e.g., using offline data exchange routines, this would be referred to as "Digital Model" or offline simulation. Rising the level of data integration to an automatic data flow from the physical to the virtual object leads to a "Digital Shadow". The virtual object (e.g., energy or heat simulation) follows the behavior of the physical object, represented through sensor data from the energy or heat network. The simulation is now online (automatically connected) to the actual sensor data. The highest level of data integration is reached when there is also an automatic data flow from the virtual back to the physical object. This closed loop data flow now enables a fully coupled status, where the behavior of the physical object (energy network) is controlled by the virtual object. This behavior is referred to as "Digital Twin". This work presents use cases for the two different situations of "Digital Shadows" and "Digital Twins". It describes the system concepts in more detail and presents implications on the development and integration of Digital Energy Twins/Shadows in real world applications. The complexity of the data management and system modeling requires specific considerations when dealing with such concepts.

2. Digital Energy Twin (DET)

The case of a "Digital Twin" is presented in Fig. 1. This case demonstrates the application of an energy-optimized production schedule. The main objective of the energy optimization is to minimize the total energy costs of the system. The main objective of the production schedule optimization is to achieve an optimal load profile of the factory. Developing a fully digital representation of the factory is challenging as modelling requires iterative development steps to improve, evaluate and revise existing models and data aggregation methods. Therefore, the Digital Twin was installed at the laboratory of FH Vorarlberg [2] focusing on a lab-scale application.

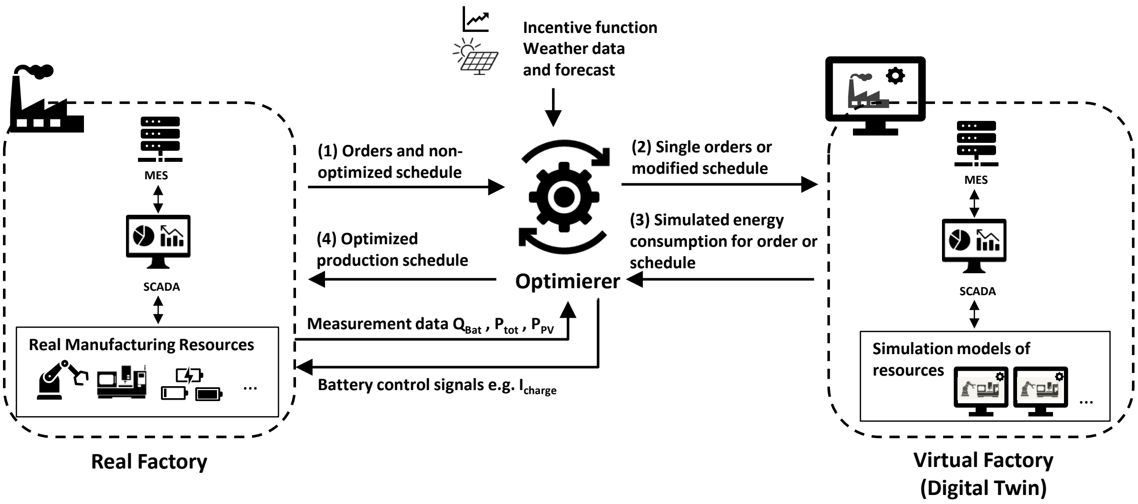


Figure 1. *Digital Energy Twin supporting decision-making on production planning.*

The Manufacturing Execution System (MES) transmits both the orders and the non-optimized production schedule to the optimizer. The optimizer utilizes the digital twin to predict the load profiles for energy consumption of various tasks. Leveraging these load profiles alongside weather data and an incentive function, the optimizer generates both the optimized production schedule and the battery operation schedule. Hence, the inputs for the optimizer include a list of jobs, estimated load profiles derived from the factory's nonlinear model, an incentive function, and weather data. Using the energy price as an incentive and the weather data as a disturbance, the production schedule and/or the battery control can be optimized. In this sense, the Digital Twin acts as input system for a model predictive (MPC) control for the real manufacturing machines. The details on the specific modeling approach are published in [3].

3. Digital Energy Shadow (DES)

The case of a "Digital Shadow" is presented in Fig. 2. Compared to the "Digital Twin" in Fig. 1, there is no data flow from the virtual system back to the real system. This use case demonstrates a design and 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.

The setup of the DES has evolved, i.e. the different modules (e.g. IoT Database, physical modelling of the energy supply system, etc.) have been developed and implemented sequentially during various stages of the project. The combination of each module finally builds up the DES itself. The modules have been tested and, in some cases, used standalone to showcase the added value and find out potential issues to be improved. The following section describe its main modules.

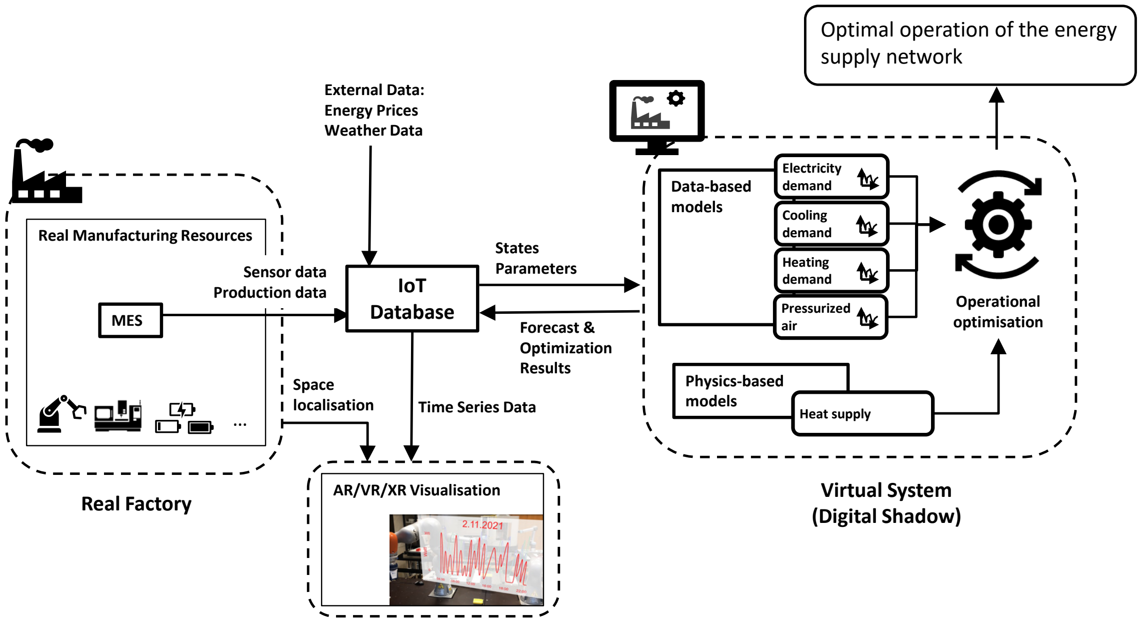
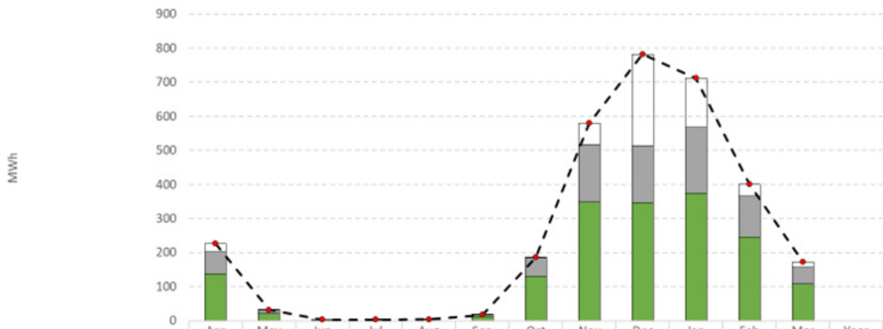


Figure 2*. Digital Energy Shadow supporting optimized operation of energy supply.*

3.1. Physical modelling of the energy supply system

The Physics-based modelling of processes and utility components was performed on AT&S' energy supply system in Hinterberg, specifically the plant 1 (Werk 1). To model the energy supply units (boiler, chillers, heat pump) mainly models of the open-source libraries Modelica Standard Library [4] (MSL) and Buildings [5] were used, e.g. BoilerPolynomial [6] and Open-Tank [7] are used to model the gas boilers and water tanks respectively. 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. Part of the validation work can be found in the final publishable report as well as in [8].



	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 3*. 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.*

The physical model has been used standalone to conduct design optimization of the energy supply system. 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 third study on the integration of a heat pump seems the most interesting one. In this case the water dumped out of the system is cooled down prior to 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 Fig. 3.

3.2. Data driven modelling of energy demand

Due to the complexity and heterogeneity of the demand side, the energy demand clusters of the various production sections have been done using data driven methods. The modelling has been done at "machine" level (e.g. at lab scale, see [9]) and at top-level, first considering the whole energy demand and then clustering the main consumers, i.e. treating the main production departments separately.

For the modelling attempt at top-level for predicting the overall energy consumption, a time series forecasting machine learning model has been used. The data was available in a 15 min 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 Fig. 4. A more detailed description on the specific model implementation is given in [2].

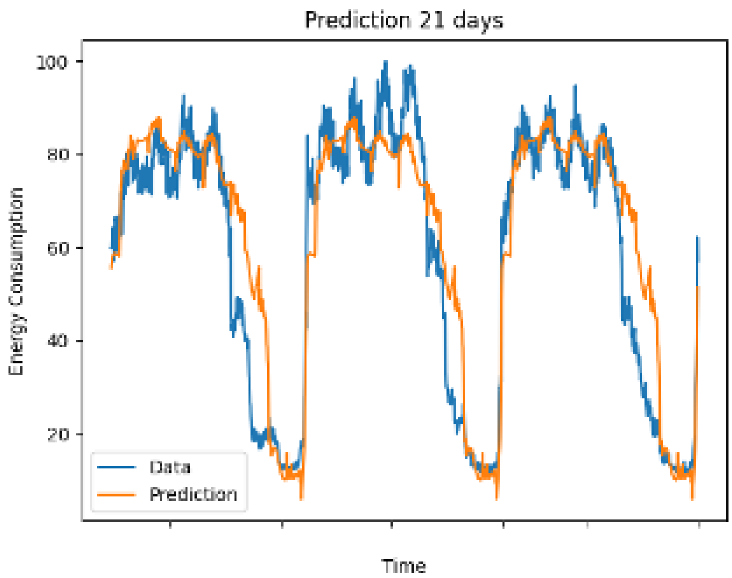


***Figure 4**. Overall energy consumption prediction [2].*

The top-level model has been refined to forecast singular consumer clusters (e.g. drilling machines). 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 program 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 on their energy demand. Exemplary results are shown in Fig. 5 for the drilling department. Specific details on the model implementation are presented in [2].

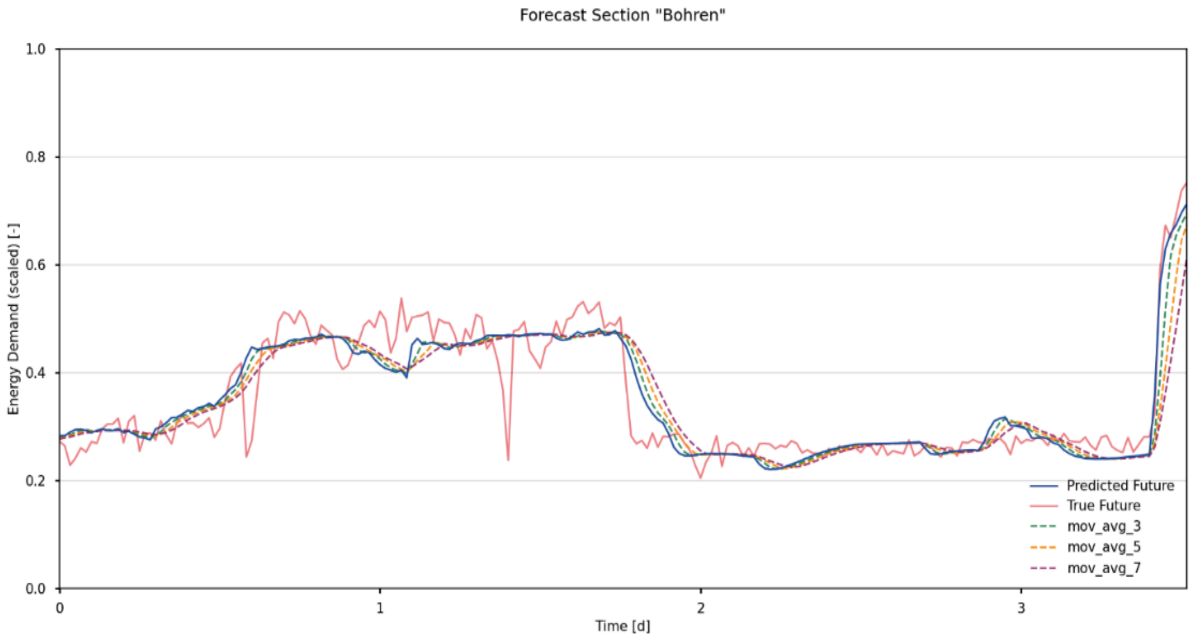


Figure 5. *Forecast of the energy consumption of the drilling department (blue line) compared to the measurements (red line) [2].*

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.

3.3. Implementation experiences

In terms of the implementation, the data acquisition process has proven to be very important. The data acquisition process of measured data is a critical aspect of such a project for its importance in the modelling and validation process as well as due to the high effort needed for data aggregation. Though the data availability within the project was good and most of the measurements needed were captured, different challenges were encountered that difficult the process to generate an industrial Digital Energy Shadow in a cost-effective way. These issues are mentioned below and should be addressed by any industrial site that envisages creating a digital shadow (or twin).

- Data availability: Relevant missing measurement points should be identified as soon as possible, and additional measurement devices should be installed.
- Data understandability: The labelling of the data should be clear enough so that the interpretation of the data can be done with as little know-how of the system as possible and therefore easily automated. Furthermore, complex system hydraulics require clearer schematics for easy understanding of the position of such sensors.
- Data access: The manual acquisition of data should be avoided. Modern databases should be used that allow the efficient and automated reading of the information required.

4. Results and Conclusion

For the lab-scale use case of the Digital Energy Twin, the energy costs of a reference scenario were compared with the energy costs for optimized battery control and production scheduling. For a time-of-use tariff the energy costs could be reduced by 8.3 % within the laboratory environment [2]. The simulations also show that production scheduling is the preferred method to reduce energy costs for the specific set-up. If uncertainties are considered, the battery storage can react to fast changes and thus is able handle disturbances and uncertainties.

The Digital Energy Shadow based on the industrial use case of company AT&S demonstrates its immediate use for design optimization purposes. 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 schadow/twin can be build. From the experiences gathered through the project, the following is concluded:

- **The use of industrial standard is key:** The modelling at system-level and also at machine level using well established communication protocols (OPC-UA, Modbus, …) is crucial for efficient implementation.
- **Physics-based and data-driven modelling** both are suitable for DET/DES applications. Each with its own advantages, drawbacks, and limitations the choice between approaches can be done individually. Important to mention is, 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 highly integrated **cloud data base** is a central part of a DET/DES and an enabler for all tasks involved in the implementation of a DET/DES.

Data availability statement

The authors do not have permission to share data.

Author contributions

Wolfgang Weiß: Project administration, Design of Methodology, Writing – original draft

Carles Ribas-Tugores: Physical modeling, Writing – original review & editing.

Competing interests

The authors declare that they have no competing interests.

Funding

This work was supported by a grant from the Austrian ”Klima- und Energiefonds-Programm Energieforschung (e!MISSION)”, FFG project number 873599.

References

[1] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification", IFAC-PapersOnLine, Bd. 51, Nr. 11, S. 1016–1022, Jan. 2018, doi: https://doi.org/10.1016/j.ifacol.2018.08.474.

[2] W. Weiß, T. Kurz, R. Hoch, et al., „Digital Energy Twin - Optimised Operation and Design of Industrial Energy Systems“, AEE INTEC, Gleisdorf, Publishable Final Project Report, to be published in 06/2024. [Online]. https://digitalenergytwin.eu/

[3] P. Wohlgenannt, M. Preißinger, M. L. Kolhe, and P. Kepplinger, “Demand Side Management of a Battery-Supported Manufacturing Process with On-Site Generation”, in 2022 IEEE 7th International Energy Conference (ENERGYCON), Mai 2022, S. 1–6. doi: https://doi.org/10.1109/ENERGYCON53164.2022.9830336.

[4] Modelica Standard Library. MSL v3.2.3, 2019. https://github.com/modelica/ModelicaStandardLibrary/releases/tag/v3.2.3.

[5] Modelica Buildings. Version 7.0.0, 2020. https://github.com/lbl-srg/modelica-buildings/releases/tag/v7.0.0.

[6] BoilerPolynomial. https://simulationresearch.lbl.gov/modelica/releases/v8.0.0/help/Buildings_Fluid_Boilers.html#Buildings.Fluid.Boilers.BoilerPolynomial.

[7] OpenTank. https://doc.modelica.org/Modelica%203.2.3/Resources/helpWSM/Modelica/Modelica.Fluid.Vessels.OpenTank.html.

[8] Carles Ribas Tugores, Gerald Birngruber, Jürgen Fluch, Angelika Swatek, and Gerald Schweiger, „Decarbonization of Industrial Energy Systems: A Case Study of Printed Circuit Board manufacturing“, gehalten auf der 14th Modelica Conference 2021, Sep. 2021, S. 497–505. doi: https://doi.org/10.3384/ecp21181497.

[9] G. Birngruber, „Digital Energy Twin: A data-driven approach to analyze and optimize industrial energy systems“, Apr. 2021, doi: https://doi.org/10.3217/r5t3q-63964.