,*Journal of Machine Engineering*, 2023, Vol. 23, No. 4, 77–88
ISSN 1895-7595 (Print) ISSN 2391-8071 (Online)

Received*: 01 September 2023* / Accepted*: 06 November 2023* / Published online: *09 November 2023*

*energy consumption, robot,
virtual commissioning,
simulation*

Leon HOLLAS[1*],
Christer-Clifford SCHENKE[1],
Arvid HELLMICH[1]

APPROACH OF A MODEL EXTENSION FOR VIRTUAL COMMISSIONING TO PREDICT ENERGY CONSUMPTION OF PRODUCTION SYSTEMS

Not only as a result of the current energy crisis, opportunities to save energy are a highly focused topic in production. For this reason, the article proposes an approach to evaluate the part-specific energy consumption of production systems by utilization of simulation methods. As an application example, a Comau 6-axis robot is chosen, of which a physically based model is created in the CAE software SimulationX. This model is then exported as a Functional Mock-Up Unit (FMU) and co-simulated within a virtual commissioning environment. Virtual commissioning enables a controller to be connected to a model. Within a Software-in-the-Loop simulation, this is a virtual control system. Based on the movement specifications from the virtual controller, the movement behaviour of the machine can be simulated in the virtual commissioning tool ISG-virtuos and the FMU returns the associated power and energy curve as a result variable. For further use, this kind of enhanced simulation models provides the possibility to optimize the utilization of production systems for specific processes in the context of a complete production line or factory.

1. INTRODUCTION

In times of global scarcity of resources, a worsening energy crisis and the resulting social burden of high living and production costs [1], considerations of energy consumption are playing an increasingly important role. According to statistics, the industrial sector accounts for a significant share of total domestic electricity and energy consumption [2, 3], which means that it also offers a high potential for optimization. Simulation can help to leverage this potential. In virtual space, different production configurations can be examined and compared with each other. The skilful coordination of processes in a production environment can lower peak loads and reduce downtime. In this way, simulation ultimately serves to identify improvements quickly and without time-consuming and costly physical interventions in production. Possible application examples are contract manufacturing in the field of CNC

[1] IIOT controls and technical cybernetics, Fraunhofer IWU, Fraunhofer Institute for Machine Tools and Forming Technology IWU, Germany
[*] E-mail: leon.hollas@iwu.fraunhofer.de
https://doi.org/10.36897/jme/174867

machining [4], assembly lines automated by robots [5] or flexible matrix production systems [6]. In order to make the most accurate predictions possible within the simulation, it is necessary to know the energy consumption of the single machines and their components during the execution of individual process steps as precise as possible.

The data- and model-based reproduction of a real production system, the so-called digital twin, enables the simulation of processes and the prediction of various indicators. Starting from these indicators, optimizations can be made in the production environment [7]. Already during process planning, several variants of machining processes can be compared and weighed against each other simulatively from the perspective of energy consumption. In order to obtain the most realistic results, the simulated machine movements should correspond to the real ones. For this purpose, simulation environments for virtual commissioning (VC) are used. Here a digital twin of the production system can be coupled to a control system. In this way exactly the control signals that will be used during the real process are used also within the simulation of it. VC environments normally do not offer the possibility of representing physical effects such as energetic behaviour. For this purpose, a model of a simulation software with a higher modelling depth can be utilized within the scope of a co-simulation. Thus, two main questions arise. First, how the energy consumption of machines can be modelled and calculated. And second, how to integrate this model into a VC environment.

2. VIRTUAL COMMISSIONING, SYSTEM- AND CO-SIMULATION

The method of virtual commissioning is a simulation-based approach for testing and commissioning of industrial controller systems. A digital twin of the machine or system is used to perform tests of the controller code with the virtual model before the implementation in the physical system takes place. This method enables early identification and elimination of errors, the reduction of commissioning time and costs, and the optimization of production processes. The key advantages of VC include its ability to provide a controlled and repeatable testing environment and the ability to simulate a wide range of application scenarios that may be impractical or unsafe to replicate in real-world conditions. VC is used in various industries, including automotive, mechanical engineering and robotics, to ensure efficient and reliable systems [8, 9].

Within virtual commissioning, a distinction is made between three different types of simulation environments depending on the representation of the control system. The simplest form is Model-in-the-Loop (MiL) simulation, in which the controller system is represented by modelled logic circuits or look-up tables within the simulation model. At a more advanced level there is Software-in-the-Loop (SiL) simulation. Here, a virtual or simulated controller is connected to the model and controls the processes within the model. As a further enhancement, there is also Hardware-in-the-Loop (HiL) simulation, in which a real control system is connected to the model and can be tested. [10]

VC models focus on simulation of the motion behaviour and the representation of sensor data. However, the model depth can be further increased by coupling other simulation models within the framework of a co-simulation. Physical based digital twins were used in Aivaliotis et al. [11] to predict remaining useful life (RUT). For this purpose, the digital twin of a robot was enriched with data from degradation curves. Ritto and Rochinha [12] applied machine learning to a dynamic physics-based simulation model. Machine learning was utilized for damage detection in this work. The aim was to use sensor data on the physical twin to make real-time statements about damage in terms of location and probability. The machine learning classifier was trained on the physics-based model for this purpose. In another scientific work, a digital twin of a robot was built to investigate the friction effects [13]. A physics-based model of rigid bodies (inertias and masses) and rotating joints was combined with a gear model that also takes into account nonlinear friction phenomena. Furthermore, physics-based simulation was used in Kaigom [14] to make a position-controlled robot manually moveable. Through manual robot guidance carried out in virtual space, a dynamically simulated robot is fed with external forces in real time. The resulting joint paths and trajectories are then returned to the real robot controller. From this point of view, many scenarios already exist in which physics-based simulation of robots has been used to gain detailed knowledge. The evaluation of energy consumption for a specific movement would be another application example here. Most physics-based simulation programs already provide everything that is necessary to compute the energy consumption of machines accurately. As a block-based system-simulation-software, SimulationX is perfectly suited for modelling physical systems. In cross-domain simulation models, e.g., mechanical, electrical, hydraulic, pneumatic, thermodynamic or magnetic effects can be described. The program offers a large number of parameterizable library blocks and the possibility to create user defined ones. By combining these blocks, the behaviour of more complex systems can be described and simulated. As example, an energy consumption model of a robot has already been implemented in SimulationX, consisting of both a mechanical and a control subsystem [15, 16].

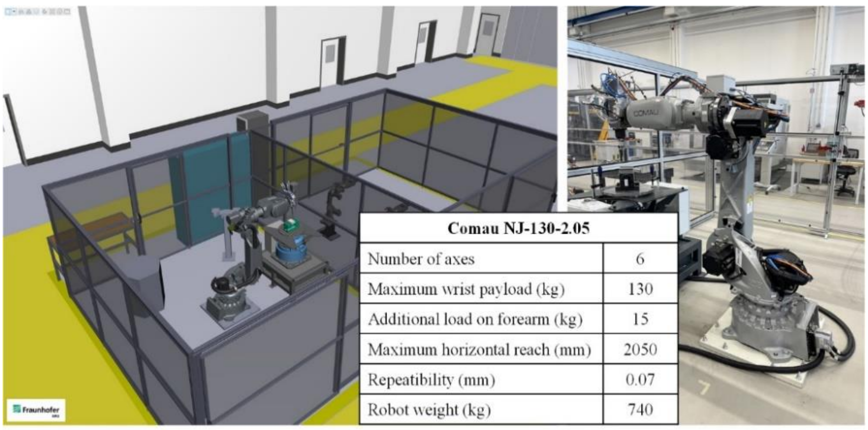
For the coupling of the VC environment and the system-simulation model, an interface is required that allows for the communication between the two simulations. The Functional Mock-up Interface (FMI) is a standardized interface for the exchange of models of different simulation software [17] and can be used for that. A functional Mock-up Unit (FMU) describes an encapsulated C-code representation of a (dynamic) system, which includes the system behaviour and is defined by inputs, outputs and other parameters. It contains differential, algebraic and discrete equations with time, state and step events. Two variants are distinguished: FMU for Model Exchange and FMU for Co-Simulation. In the Model Exchange variant, the system is solved by the integrator of the environment in which it is embedded. In the Co-Simulation variant each subsystem is calculated by its own solver. In this setup a simulation master controls the data exchange between the individual subsystems and ensures the synchronization of the time steps in the subsystems [17].

3. OBJECTIVE

For the future of the industry, energy efficiency plays a significant role in achieving sustainability and cost-effectiveness. Machines and the processes carried out on them will also have to be considered and evaluated in terms of energy aspects. Therefore, a new approach for simulating energy consumption in a virtual commissioning environment is proposed. Conventional energy simulation techniques often lack the granularity required to identify the specific energy consumption for the execution of a process. Either simplified models with a low temporal resolution are used [18] or the energy consumption is assumed as constant for defined states of the production machine [19]. To address this research gap, a simulation environment is developed in which a high-resolution energy consumption model is integrated in a simulation tool for virtual commissioning. The virtual commissioning software will serve as a powerful tool for simulating and analysing various operational scenarios using the real control specifications. Using the example of a six-axis robot a high-resolution physics-based model is developed that can accurately determine the energy consumption for the machine and its axes. This model is integrated in the VC environment using an FMU to generate a suitable simulation environment. The aim of the work is to find suitable simulation step sizes for the used solvers in the VC tool and the FMU to ensure accurate calculation of energy consumption.

4. METHODS

A significant part of the energy consumption in the industrial sector is caused by automation equipment such as robots [20]. As robots are used in many different ways in industry and are steadily increasing in their prevalence, a robot cell (Fig. 1) was chosen as an application example for this work. In this cell, a Comau NJ 2.05 robot that is equipped with a CNC-control performs milling operations. A clamping table is used to pick up and clamp the workpiece.



Comau NJ-130-2.05	
Number of axes	6
Maximum wrist payload (kg)	130
Additional load on forearm (kg)	15
Maximum horizontal reach (mm)	2050
Repeatibility (mm)	0.07
Robot weight (kg)	740

Fig. 1. Robot cell used as application example

4.1. ENERGY CONSUMPTION MODEL

To create the SimulationX model of the robot, the kinematic chain consisting of six individual axes is first modelled. Figure 2 shows the resultant model and a definition of the robot's axes. Each yellow block in Fig. 2 contains the geometry information of the corresponding axis. The definition of masses and inertia tensors of the individual components is based on the CAD data.

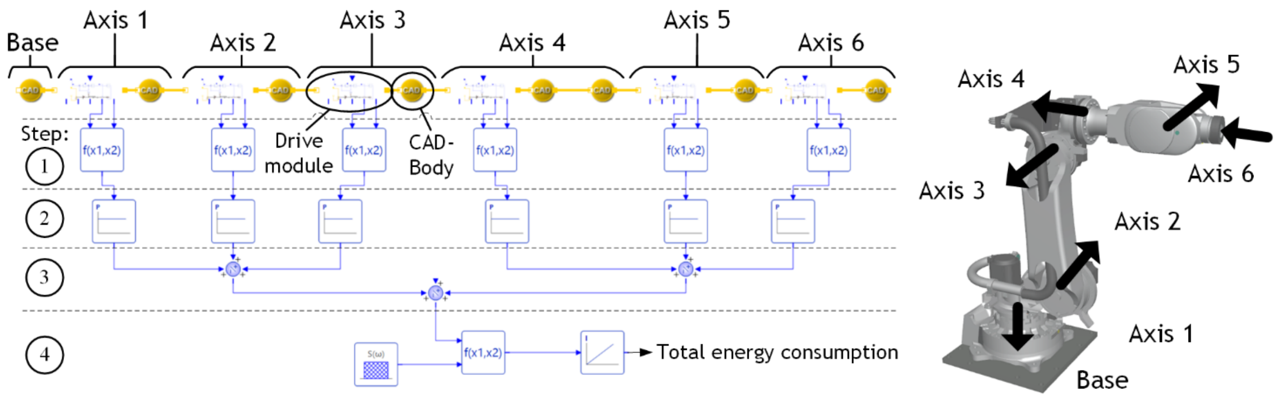


Fig. 2. Physical model of the 6-axis Comau robot modelled in SimulationX

The individual elements of the kinematic chain are coupled via a drive module that contains a joint, the gear, the motor as well as the controller structures (Fig. 3). The drive control is modelled in a simplified way, consisting of a cascade control without the representation of a current controller. Simple P controller are used as position and speed controller [21]. The comparison between target and actual position takes place on the drive side, i.e., before the gear ratio (Fig. 3). In order to be able to compare the position specification, which refers to the joint, with the drive side, the target value must first be amplified with the transmission ratio.

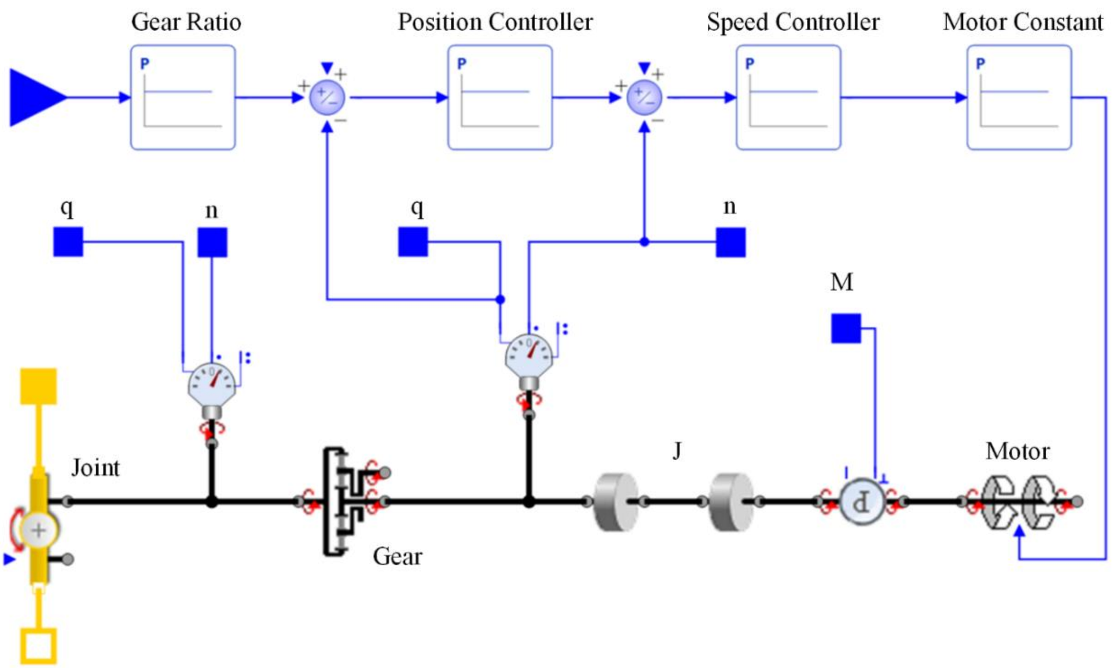


Fig. 3. Drive module with control loops, inertias, gear and joint

For the parameterization of the model, the values from the type plates of the motors and similar motors are included. The control elements involved are initially parameterized on the basis of values stored in the real controller.

The joints are assumed to be frictionless, which keeps the computational effort within limits. Especially for the later use in a virtual commissioning environment, quantities like computation times are relevant. Instead, the friction losses, which have a significant influence on the energy consumption of the robot, are indirectly captured via the efficiency (formula (2)). The same problem concerns heat losses, the modelling of which would be very complex and would significantly slow down the calculation of energy consumption. By calibrating the model to the measurement (Section 4.2) and adjusting the parameters, thermal losses are captured as well.

To evaluate the energy consumption the mechanical parameters of the drive are used. The drive module gives back torque and motor speed from which mechanical power is calculated (Fig. 2: Step 1) according to formula (1).

$$P_{\mathrm{mech}} = 2 * \pi * M * n \tag{1}$$

Using the efficiency which describes the losses (mainly friction and heat) between the two physical domains, this is converted into an electrical power (Fig. 2: Step 2).

$$P_{\mathrm{el}} = \frac{1}{\eta} * P_{\mathrm{mech}} \tag{2}$$

The electrical power of all individual axes is summed up (Fig. 2: Step 3) and then added to the experimentally determined basic load of the system (Fig. 2: Step 4). Afterwards this is integrated to the total energy of the certain movement (formula (3)).

$$E_{\mathrm{el}} = \int \sum_i P_{\mathrm{el},i} + P_{\mathrm{base}}\, dt \tag{3}$$

4.2. COMPARISON BETWEEN SIMULATION AND ENERGY MEASUREMENT RESULTS

To be able to assess the quality of the simulation results, the energy consumption on the machine must be measured. A mobile measuring device from the company Dewetron was used for this purpose. The DEWE-2600 measures the current and voltage of each individual phase at the feeding point of the robot, calculates apparent, active and reactive power as well as energy consumption and outputs these values over time.

The first measurements recorded the idle mode of the robot. All active components of the robot cell were switched on, but the robot did not move. This indicates the base load of the machine and its peripherals and allows the value to be taken into account in the model. The consideration of the base load was done by adding it to the sum of the power of all axes.

In the next step the program for a milling pocket was executed. However, this was only the path, without actually milling. The records showed that the measured power curve during the movement of the milling process closely matches to the measured power curve in idle mode. There were only visible power peaks when the robot starts moving or moves to the rest position. Due to the only small movements to perform the milling path, the power values oscillate around the peripheral base load. This makes a subsequent model alignment on the basis of this measurement data extremely difficult.

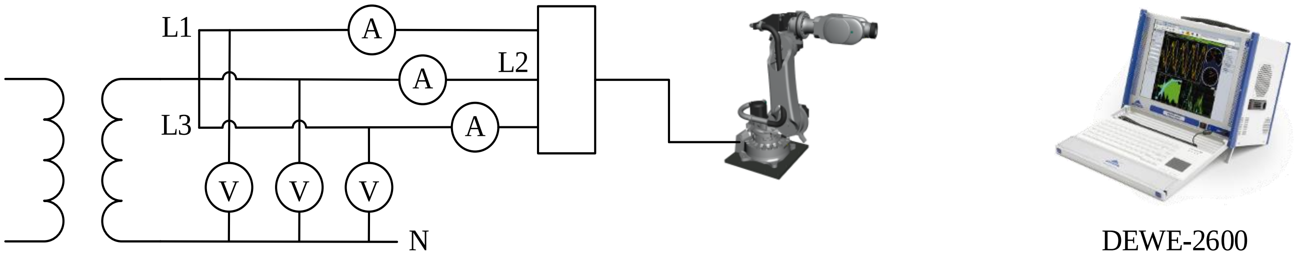


Fig. 4. Structural measurement setup and measured variables

Therefore, a new movement specification had to be defined. Each individual axis was moved at maximum speed and acceleration from 0° to 30° to -30° and back to 0° again. This allows to evaluate each axis independently of the others. In addition, the power required to perform this movement is high enough so that it can be identified within the measured curves. The measurement was repeated three times to have a statistical confidence.

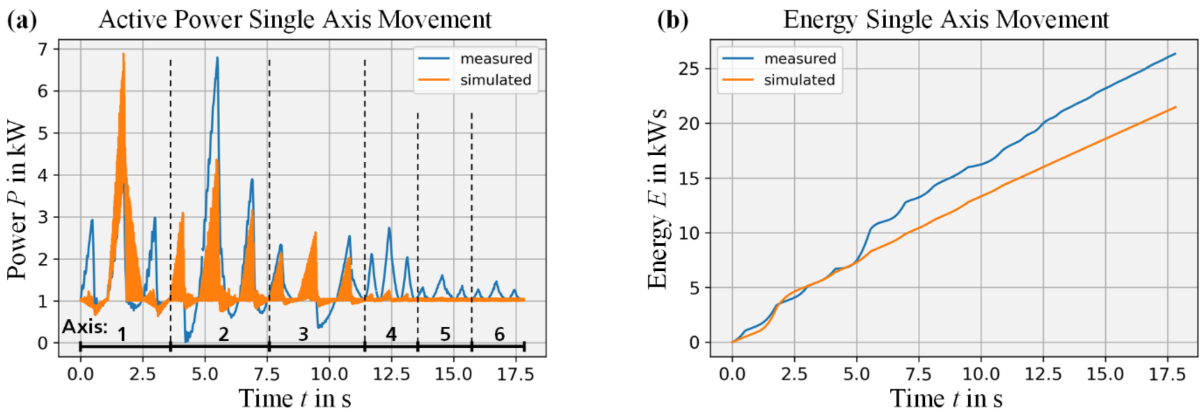


Fig. 5. Comparison of measurement and simulation for robot movement: (a) power curve, (b) energy consumption

After running the same single axis movement in the simulation as well, the results between measurement and simulation can be compared. The power curve (Fig. 5a) and energy consumption (Fig. 5b) are displayed graphically for visualization purposes. The measured curves are shown in blue and the simulated curves in orange. In Fig. 5a it is noticeable, that high-frequency oscillations occur in the simulated power curve, which indicates a poor controller setting. In addition, the simulated power curve, especially for axes four, five and six, is below the measured curve (Fig. 5a for $t \geq 11$ s). The deviations of the power curve are also visible in the energy consumption Fig. 5b, the time integral of the power. The measured and simulated energy consumption increasingly diverge over time.

4.3. MODEL ALIGNMENT

To overcome the large discrepancies between the simulation and the measurement, it is necessary to perform a model adjustment. On the one hand, the controller parameters were adjusted to get rid of the oscillations in the simulated power curve. Oscillations in controlled systems are often caused by incorrect controller settings. Consequently, the amplification coefficients of the P-controller in the model were adjusted until high-frequency oscillations no longer occurred. To fit the power curve for the operation of the axes, the inertias in the model were adjusted so that the peaks of the measured power curve are also achieved in the simulation results. Since no exact values could be determined for the motors which were specially made for the robot manufacturer, one of the uncertainties in the model are the values of the inertias which have direct influence on the amplitude of the power.

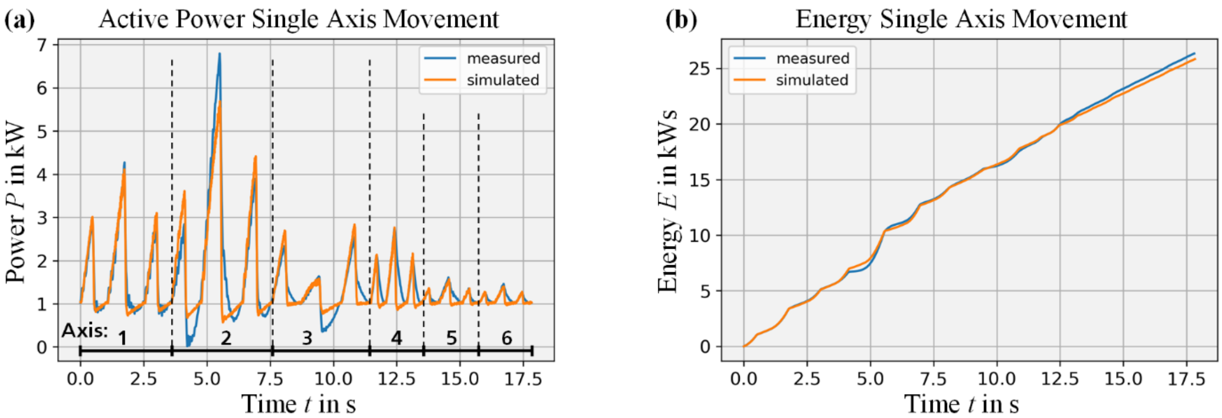


Fig. 6. Comparison of measurement and simulation for the aligned model: (a) power curve, (b) energy consumption

After the adaption of the controller parameters and the inertias, a clear similarity between the measured and simulated power curve can be observed (Fig. 6a). In particular, the energy curves (Fig. 6b) show very good match and only slight deviations. The relative error in the energy curve is below 3% almost all the time. It only exceeds this limit at about $t = 5$ s for the movement of axis 2. The energy recovery by the drives is probably greater in reality than in the model in certain cases. Within the current model there is no possibility to take this varying energy recovery into account. More precise modelling of the drives may solve these deviations, but the focus in this work is on the energy consumption of the whole machine, which fits in total. Now that it is ensured that the model provides values comparable to the measurement, it can be used for the integration into the VC environment.

4.4. CONNECTION OF THE SYSTEM-SIMULATION MODEL AND THE VIRTUAL COMMISSIONING TOOL

The tool ISG-virtuos for virtual commissioning is used to visualize and analyse the motion behaviour of the robot using control specifications provided by an industrial controller. In the presented use case, a virtual controller (Fig. 7 on the left) is connected to the

VC model and provides the position specifications. So, e.g., plausibility checks of the controller code and the test of collisions can be done with the virtual kinematics. In order to couple the energy consumption model with the software for virtual commissioning, the standardized interface FMI was used. Since the ISG-virtuos only supports FMUs for Co-simulation, the SimulationX model of the robot was packed into one accordingly. The interaction with the model in the FMU is done by defined input and output ports. These ports are used to establish a connection to the virtual commissioning model (Fig. 7). As input signals the target positions of the individual axes are used. The power and energy curves are available as outputs. FMUs can contain parameters as well. In this use case the efficiency of the servo motors or the level of the base load can be adjusted by the parameters.

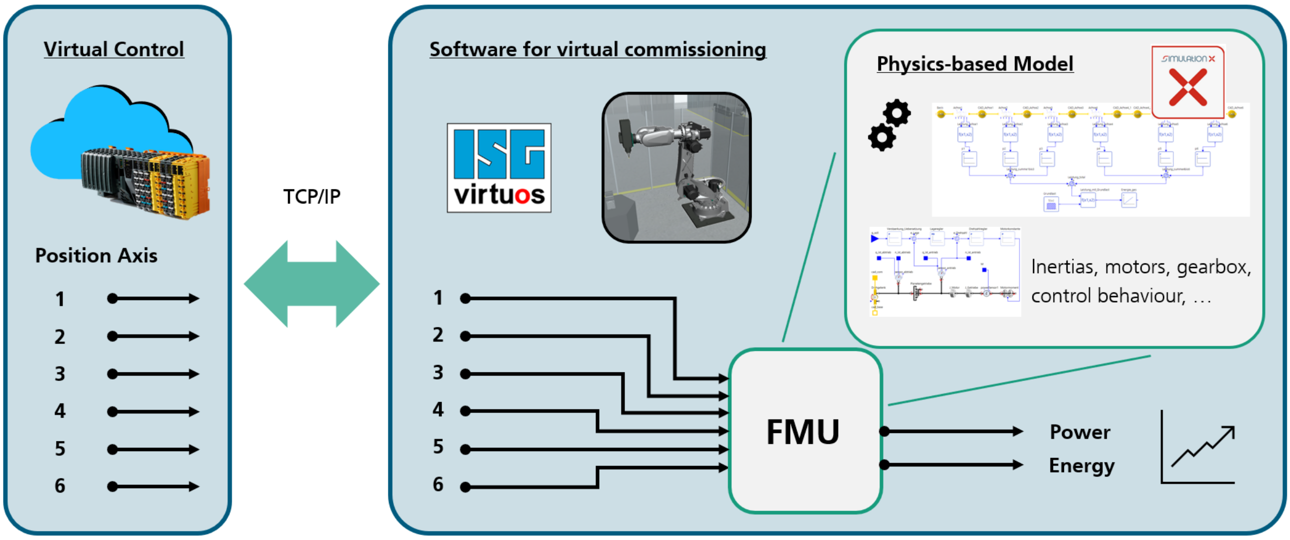


Fig. 7. Structural design of the SiL simulation in the virtual commissioning environment

4.5. RESULTS

The described simulation environment now allows for a co-simulation of the VC model for the kinematic behaviour and the system-simulation model for the energetic behaviour both using controller setpoints as input. A Model-in-the-Loop approach was used for the initial analysis of the behaviour of this simulation environment.

The VC tool includes its own solver and acts as the simulation master, while the FMU acts as the slave (Fig. 8). Since an FMU for Co-simulation is used, it also contains its own solver. Consequently, suitable simulation step sizes have to be defined for each solver. To check the accuracy of the energy consumption calculation in the co-simulation, the simulation step size dt_{slave} of the FMU was set to 10 ms. This step size was used also in the SimulationX Model on which the FMU bases. The first approach was to let the simulation master and the simulation slave calculate at the same step size ($dt_{\text{master}} = dt_{\text{slave}}$). With this setting, the results of the FMU (Fig. 9: blue curve) showed very strong deviations from the results of the SimulationX model (Fig. 9: black curve). By decreasing the simulation step size of the virtual commissioning tool (master) to 1 ms (Fig. 9: orange curve), the results get closer to those of the model. If the simulation step size is then reduced even further to 0.1 milliseconds, the results of the FMU (Fig. 9: green curve) correspond to those of the model (Fig. 9: black curve). This leads to the conclusion that in this case, reducing the simulation step size of the simulation master by around two orders of magnitude compared to the step size of the simulation slave results in a more accurate calculation of the energy consumption.

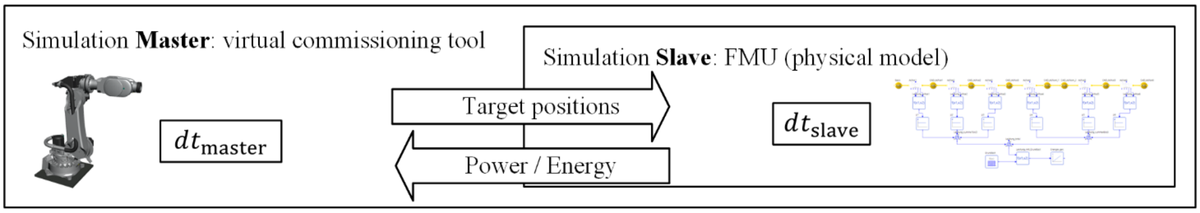


Fig. 8. Master-slave arrangement in the Co-Simulation and exchanged variables

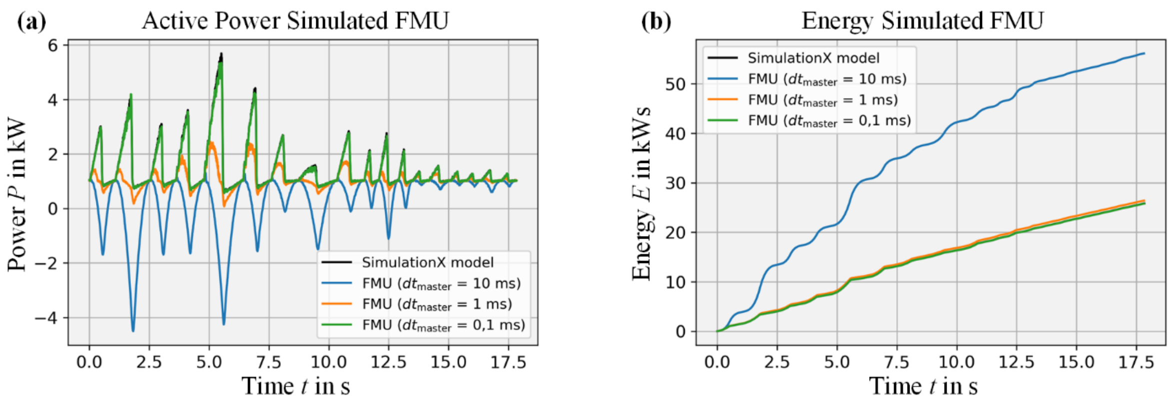


Fig. 9. FMU results for different simulation step sizes of simulation master: (a) power curve, (b) energy consumption

5. CONCLUSION

It was shown that a model for calculating energy consumption can be integrated into an environment for virtual commissioning. This makes it possible to evaluate energy consumption directly based on the control code. To optimize energy consumption, it is conceivable to modify the control code, for example by moving to a position using the movement of other axes, and then to compare it simulatively in order to estimate the potential for improvement. The approach presented also allows the same control code to be compared on different digital machine twins in terms of the energy required. This helps with decision-making in production planning or when deciding which machine should be used.

For the exact mapping of the base load and the adjustment of the model for the energy consumption calculation, a measurement of the real system is still necessary as a basis. At this point, however, it must be mentioned that for the work presented a Model-in-the-Loop simulation was used. For the use of the simulation environment in a Software-in-the-Loop simulation, the Transmission Control Protocol (TCP) connection used so far between the virtual controller and the virtual commissioning (VC) tool appears to be unsuitable. There is currently the need for further investigation here.

As further work, the system simulation model will be qualified on the basis of complex robot movements with superimposed movements of the individual axes. The consideration of the process and the process forces will also lead to an increase in the informative value of the models. This will enable machine manufacturers and users to evaluate the efficiency of different control strategies in order to investigate approaches for optimization and energy savings.

REFERENCES

[1] GANGL K., et al., 2022, *Policy Brief: Energiekrise – was tun?*, Institut für Höhere Studien, Vienna.
[2] BDEW, 2021, *Verteilung des Stromverbrauchs in Deutschland nach Verbrauchergruppen*, im Statista, 2022, [Online], Available: https://de.statista.com/statistik/daten/studie/236757/umfrage/stromverbrauch-nach-sektoren-in-deutschland/.
[3] Statistisches Bundesamt, 2023, *Energieintensivste Produktionsbereiche nach Energieverbrauch in Deutschalnd im Jahresvergleich 2010 und 2020,* [Online], Available: https://de.statista.com/statistik/daten/studie/ 164011/ umfrage/ energieintensivste-und-energieaermste-industrien-deutschland-2008/.
[4] GOLLEE C., SELCH M., SCHENKE C.-C., HELLMICH A., IHLENFELDT S., 2022, *Learning Robots for the Machining of Easily Machinable Materials Situationally Optimal Robot Models*, (in ger), *AT-AUTOM*, 70/6, https://doi.org/10.1515/auto-2021-0162.
[5] FRITZSCHE R., RICHTER A., PUTZ M., 2018, *Product Flexible Car Body Fixtures with Methods of Artificial Intelligence*, Procedia CIRP, 67, https://doi.org/10.1016/j.procir.2017.12.241.
[6] IHLENFELDT S., et al., 2021, I*ncreasing Resilience of Production Systems by Integrated Design*, *Applied Sciences*, 11/18, 8457, https://doi.org/10.3390/app11188457.
[7] TAO F., XIAO B., QI Q., CHENG J., JI P., 2022, *Digital Twin Modeling*, Journal of Maufacturing Systems, 64, 372–389, https://doi.org/10.1016/j.jmsy.2022.06.015.
[8] KRYSTEK J., ALSZER S., BYSKO S., 2019, *Virtual Commissioning as the Main Core of Industry 4.0 – Case Study in the Automotive Paint Shop*, Advances in Intelligent Systems and Computing, Intelligent Systems in Production Engineering and Maintenance, A. Burduk, E. Chlebus, T. Nowakowski, and A. Tubis, Eds., Cham: Springer International Publishing, 370–379.
[9] METZNER M., et al., 2020, *A System for Human-in-the-Loop Simulation of Industrial Collaborative Robot Applications*, IEEE 16th International Conference on Automation Science and Engineering (CASE), https://doi.org/10.1109/CASE48305.2020.9216766.
[10] WÜNSCH G., 2007, *Methoden für die Virtuellen Inbetriebnahme Automatisierter Produktionssysteme*, *TU München*, ISBN 978-3-8316-0795-2.
[11] AIVALIOTIS P., ARKOULI Z., GEORGOULIAS K., MAKRIS S., 2021, *Degradation Curves Integration in Physics-Based Models: Towards the Predictiv*e *Maintenan*ce of *Industrial Robots*, Robotics and Computer-Integrated Manufacturing, 71, 102177, https://doi.org/10.1016/j.rcim.2021.102177.
[12] RITTO T.G., ROCHINHA F.A., 2021, *Digital Twin, Physics-Based Model, and Machine Learning Applied to Damage Detection in Structures*, Mechanical Systems and Signal Processing, 155, 107614, https://doi.org/ 10.1016/j.ymssp.2021.107614.
[13] AIVALIOTIS P., KALIAKATSOS-GEORGOPOULOS D., MAKRIS S., 2023, *Physics-Based Modelling of Robot's Gearbox Including Non-Linear Phenomena*, International Journal of Computer Integrated Manufacturing, 1–12, https://doi.org/10.1080/0951192X.2022.2162594.
[14] KAIGOM E.G., ROßMANN J., 2017, *Physics-Based Simulation for Manual Robot Guidance—an eRobotics Approach,* Robotics and Computer-Integrated Manufacturing, 43, 155–163, https://doi.org/10.1016/j.rcim. 2015.09.015.
[15] ZHAO S.J., SHAN J.Y., BI L.Y., 2012, *6-axis Serial Robot Simulation Based on Simulationx*, *AMM*, 152–154, 1010–1017, https://doi.org/10.4028/www.scientific.net/AMM.152-154.1010.
[16] BI L., LIU L., 2011, *4-Axis Robot Design and Simulation Based on SimulationX*, First International Conference on Robot, Vision and Signal Processing, Kaohsiung City, Taiwan, Nov. - Nov. 2011, 65–68.
[17] Modelica Association Project FMI, *Functional Mock-up Interface* 2.0.3.
[18] HEINZL B., KASTNER W., LEOBNER I., DUR F., BLEICHER F., KOVACIC I., 2014, *Using Coupled Simulation for Planning of Energy Efficient Production Facilities*, Workshop on Modeling and Simulation of Cyber-Physical, IEEE, https://doi.org/10.1109/MSCPES.2014.6842397.

[19] SCHLEGEL A., STOLDT J., PUTZ M., 2013, *Erweiterte Integration energetischer Betrachtungen in der Materialflusssimulation*, Simulation in Produktion und Logistik Entscheidungsunterstützung von der Planung bis zur Steuerung Wilhelm Dangelmaier, Christoph Laroque & Alexander Klaas (Hrsg.) Paderborn, HNI-Verlagsschriftenreihe 2013.
[20] MEIKE D., RIBICKIS L., *2011, Industrial Robot Path Optimization Approach with Asynchronous Fly-By in Joint Space*, IEEE International Symposium on Industrial Electronics, Gdansk, Poland, Jun. 2011, 911–915.
[21] CHESMOND C.J., 1982, *Control System Technology*, Elsevier Ltd, ISBN 978-0-7131-3508-4, https://doi.org/10.1016/C2013-0-06419-5.