Implementation features of local and remote technical objects digital twins

Vladyslav Pliuhin, Maria Sukhonos, Ihor Biletskyi, Sergiy Plankovskyy, Yevgen Tsegelnyk*

School of Energy, Information and Transport Infrastructure,
O.M. Beketov National University of Urban Economy in Kharkiv,
17 Chornohlazivska Street, Kharkiv 61002, Ukraine

* E-mail: y.tsegelnyk@kname.edu.ua

Abstract. This paper explores the potential for implementing digital twin technology, focusing on the internal structure of the research object and the remote characteristics of its surrounding environment. Specifically, it examines and demonstrates the practical application of local digital twins, which replicate the object's structural parameters using data from sensors and measurement devices positioned at key nodes within the research object. Another category of digital twins leverages data collected from instruments measuring external environmental conditions and falls under the classification of remote digital twins. When combined, these local and remote digital twins create a comprehensive framework for predictive decision-making, assessing both the current status of the object and potential outcomes in emergency situations. This study seeks to explore the feasibility of integrating digital twins across various hierarchical levels of the research object. The findings presented in this paper represent the authors' practical innovations, which demonstrate effective outcomes and offer a foundation for advancing research objectives in this area.
Key words: digital twin, virtual model, remote control, energy efficiency, digital platform.

1. Introduction

Digital twins (DT) are a concept that refers to a pair or group of structurally similar elements in a digital environment [1, 2]. It can be two identical files, programs or other objects that perform similar functions or have a similar structure [3]. For instance, in the field of electromechanics, which constitutes the primary scientific focus of the authors of this paper, digital twins can be utilized to develop object-oriented models of electromechanical energy converters and their assemblies. [4]. This makes it possible to analyze their work, solve problems without directly interfering into the real object [5, 6].

The DT can display the operation of the electric motor, its temperature state, consumed energy, etc. This is useful for improving the operation of the system, preventing possible breakdowns, and increasing the efficiency of using electromechanical devices [7–10].

Regarding the questions discussed in this paper, such type of DT can be characterized as "local." Figure 1 presents an example of constructing a DT of an induction motor, integrated into ANSYS Twin Builder software simulation workspace. In this context, the DT serves as a virtual model of a functional physical structure, calculating the current state parameters while considering the actual history of changes, mode of work, and operating conditions of the object (system).

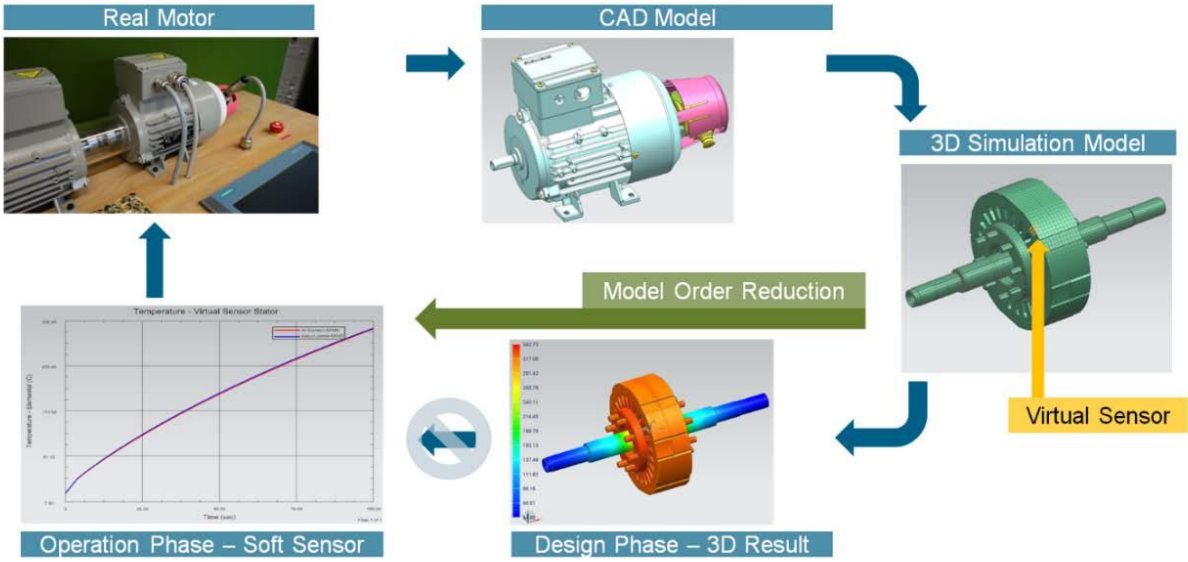

Figure 1. Digital twin of an induction motor with a squirrel-cage rotor.

The development of the virtual model is based on the creation of Reduced-Order Model (ROM), which in this example was built on the base of an induction motor with a squirrel-cage rotor. The DT facilitates the design, predictive maintenance, and optimization of control for industrial systems [11–14]. Figure 2 illustrates the use of a DT to determine the life of a lithium-ion battery, supported by ANSYS Thermal IcePak LTI Battery Module ROM and ANSYS Twin Builder to swiftly address transient temperature control issues [15, 16]. Figure 3 demonstrates a more advanced system, employing a complex of local DT to replicate the automation and power system of an electric vehicle.

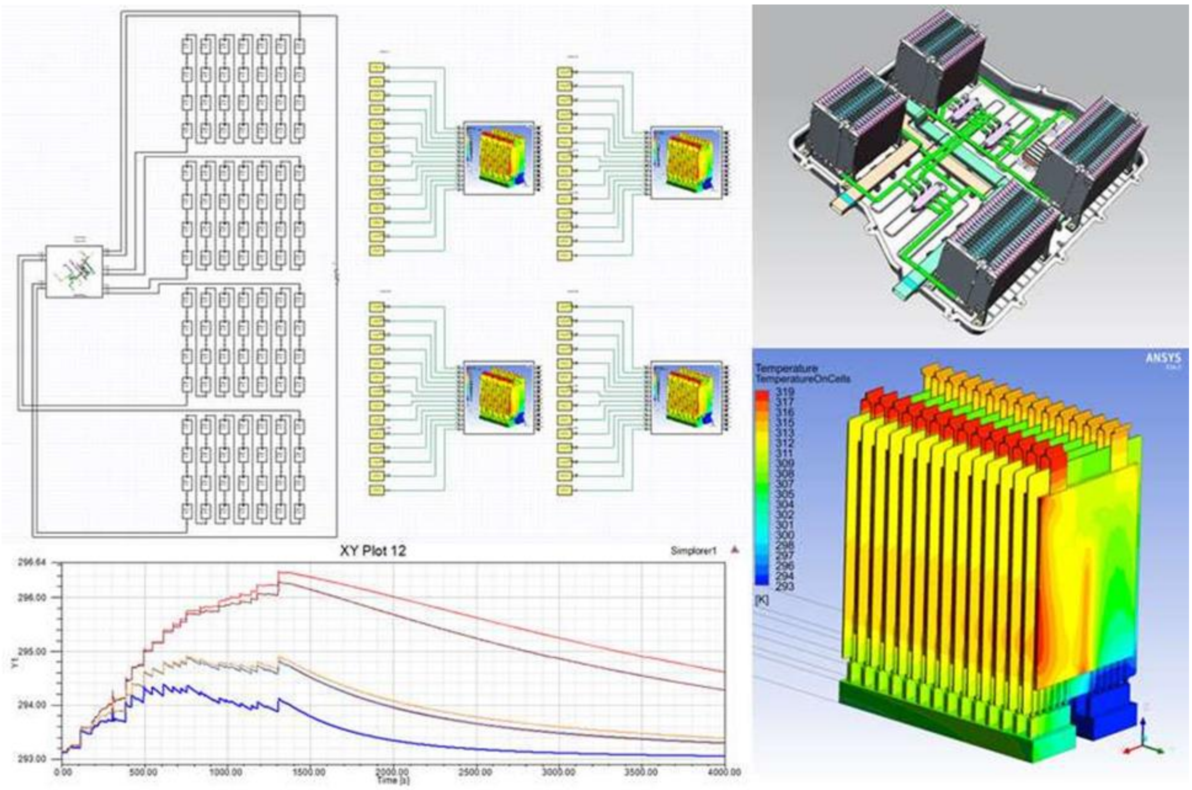

Figure 2. Analysis of the lithium-ion battery thermal state and life cycle.

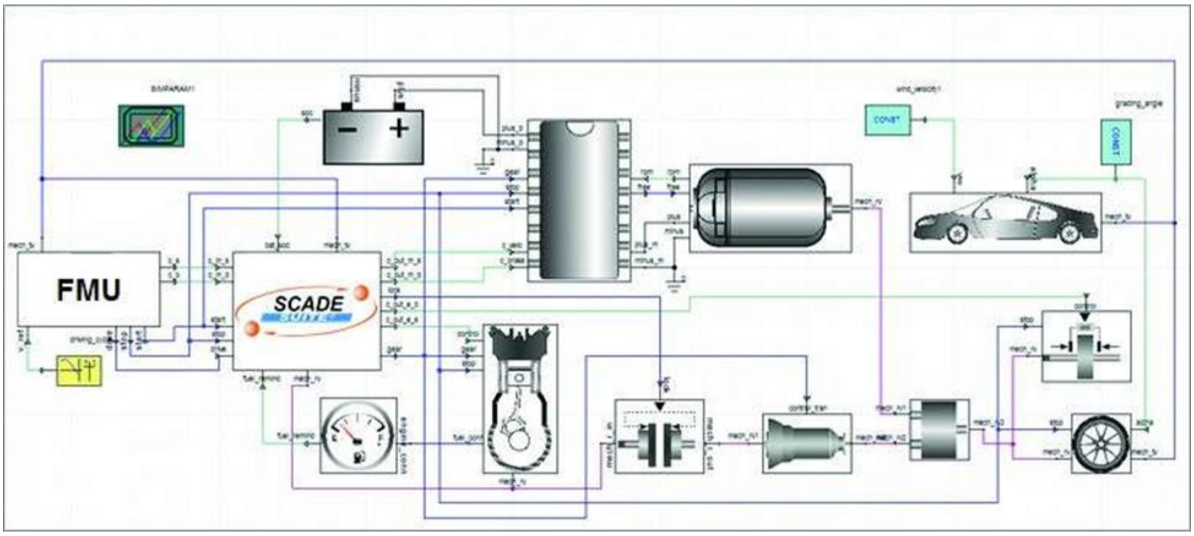

Figure 3. Debugging the software built into the hybrid car system using ANSYS SCADE.

On the example of remote objects, the most notable solution is the DT of a city's energy system. Digital twins in the electric power sector are a crucial tool that revolutionizes the traditional methods of managing and monitoring power systems. With the help of DT, it is possible to represent computer aided AI duplicates of power plants, back-bone networks, and other infrastructure components [17–20].

The first application aims to enhance the management of energy facilities. Digital twins enable real-time modelling and monitoring of power plant operations, production forecasting, and parameter adjustments for optimal efficiency. This improves reliability and reduces energy consumption [21]. A second significant application is in electric power distribution management. Digital twins can optimize back-bone networks by considering factors such as transmission quality and power consumption. This helps prevent overloads and ensures stable system operation under variable load conditions. [22].

Another important factor is the enhancement of transmission network energy efficiency. Digital twins can control equipment modes, identify more efficient operation conditions, and suggest optimizations to reduce energy consumption [23]. Additionally, DT in the electricity sector is used to forecast and manage electricity demand, assess the impact of renewable energy sources, and implement "Smart Grid" technologies. These advancements serve to create a endurable, energy-saving, and green electric power system.

Digital twins are not limited by one object. At instance, even if a factory has two similar pumps, they can have different working modes, loads and reliability parameters. Consequently, for each pump we will develop a separate DT. Sensor data from each pump will enable the simulation software to provide personal regression analysis for each unit. At the other hand, DT for in the scale of whole city form the digital models that assist in optimizing various aspects of the urban environment. For example, they can simulate traffic patterns to enhance traffic flow management and forecasting. Digital twins can also be used for virtual modelling of building energy consumption, water supply and drainage planning, as well as managing city security systems and waste. These models support city authorities in making informed and effective decisions to improve urban living conditions.

In more complicated case, nuclear power plants (stations) feature numerous subsystems that could each become separate DT, that resulting in creation of thousands individual models. Once we master the deployment of these DT for such industrial facility, we can also transfer an obtained experience on the base of machine learning trained models to other large and complex systems, such as nuclear submarines or metal-works plants. The nuclear industry is particularly suited for modelling because there are many aspects that cannot be physically tested.

The currently existing solutions that ANSYS provide for complex facilities can be expanded to other safety-critical industries. These industries include aerospace, conventional and renewable energy, and the broader automobile sector, especially in the realm of rising accumulator batteries sector. Mentioned systems present crucial challenges due to their numerous issues with their internal subsystems and mutual influence of internal parameters.

Active research by scientists is directed at solving the intricate problem of identifying electrical power objects. This research includes a range of papers focused on developing decision-making models that use digital meters data to predict parameters and working modes of technical objects as well as facilities with subsystems based on individual factors, receiving from each system node.

In this article the main purpose of research consists in analyzing possibilities and practical realization of the DT approach to build city internal and external infrastructure objects virtual models.

2. Formation and characteristics of digital twins

A digital twin is a virtual representation of a physical object, system, or process. It integrates real-time data from sensors and other sources to mirror the current state and behavior of its physical counterpart, allowing for simulation, analysis, and optimization. A digital twin is a dynamic, digital replica of a physical entity or system. It uses data collected from the physical object through sensors and other inputs to create a virtual model that can be analyzed, monitored, and manipulated.

ANSYS Twin Builder is a comprehensive tool designed for developing, deploying, and managing digital twins. It offers a range of features and capabilities to support various aspects of the DT lifecycle. ANSYS Twin Builder is a powerful tool for creating and managing digital twins, offering extensive capabilities from multi-physics modeling to real-time data integration and predictive analytics. Its features support a wide range of applications across various industries, making it a key solution for advancing DT technology [14]. Figure 4 shows an example of DT built for solving Multiphysics task of induction motor with squirrel-cage rotor, its control and electric drive system

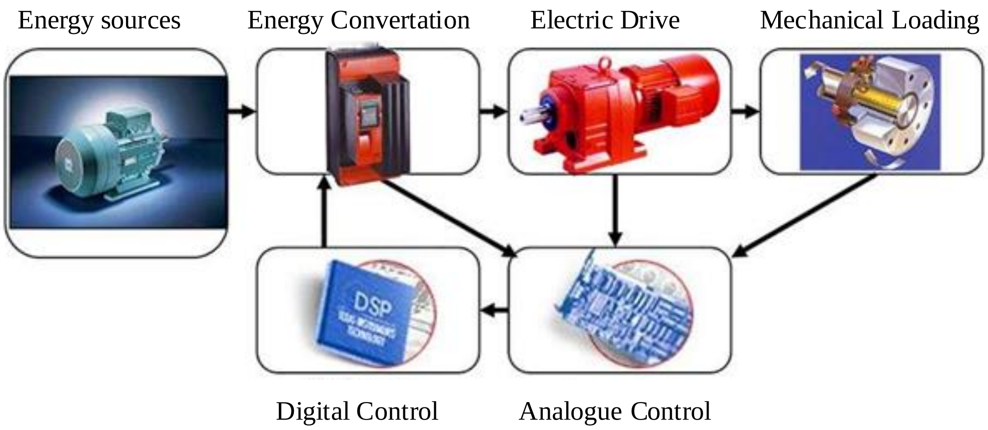

Figure 4. Digital twin of Multiphysics system domain.

ANSYS Twin Builder capabilities are presented in a Table 1. Creation of DT that combine various physical domains such as structural mechanics, fluid dynamics, and thermal analysis can be useful in Multi-Physics Modeling. ANSYS Twin Builder supports coupling between different physics models to provide a holistic representation of the system (Figure 5). Access of pre-built libraries of components and systems intended to accelerate model development. These libraries include templates for common components and subsystems. Such scientific platform integrate with CAD (Computer-Aided Design) and CAE (Computer-Aided Engineering) tools for importing geometry, design details, and simulation data.

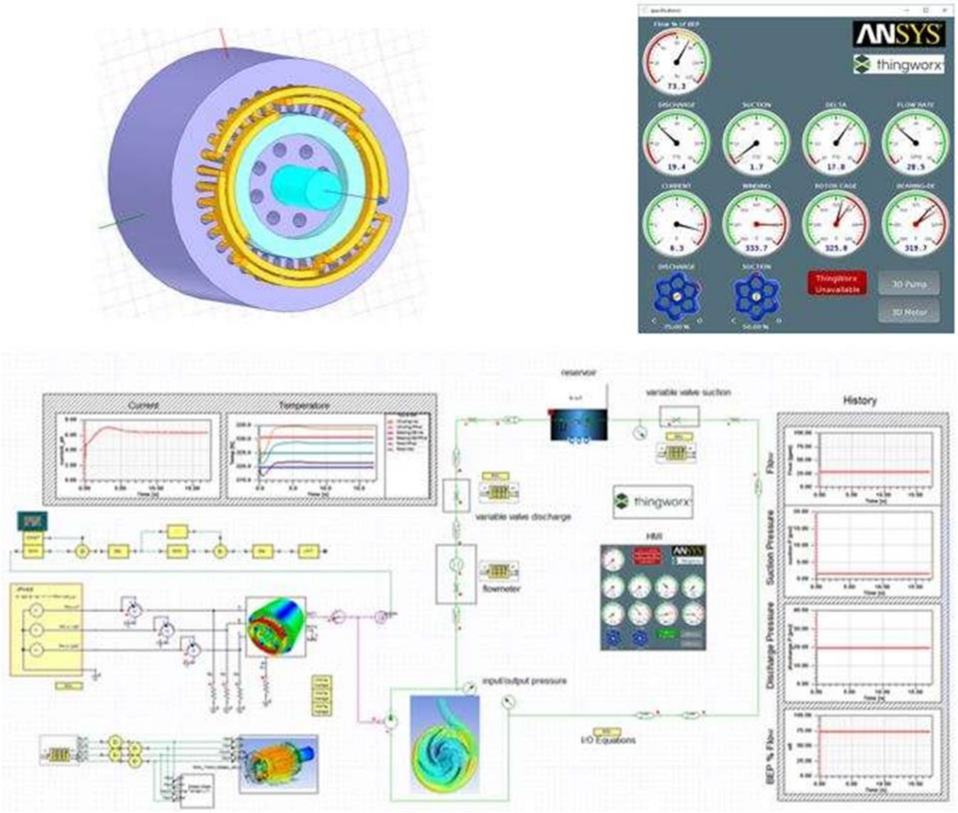

Figure 5. Coupling project of an electric motor cooling system in ANSYS Twin Builder.

Table 1. Visualization of ANSYS Twin Builder Capabilities.

Capability	Description	Examples
Model Creation	Multi-physics modelling, component libraries, system modelling	Power plant simulations, CAD integration
Data Management	Real-time data integration, data assimilation, analytics	Sensor data analysis, predictive maintenance
Simulation	Scenario simulation, optimization, failure analysis	Load testing, component failure assessment
Deployment	Digital twin deployment, lifecycle management, cloud/on-premises options	Operational monitoring, model updates
Collaboration	Collaborative workspaces, version control	Team-based projects, model revisions
Advanced Features	Digital twin templates, advanced technology integration, compliance	AI integration, industry standard adherence

Digital twins are sophisticated virtual models that replicate the behavior and state of physical objects, systems, or processes. The creation and operation of digital twins rely heavily on mathematical principles from various fields, encompassing core areas such as system modeling, data assimilation, optimization, and predictive analytics. At the heart of DT technology is a system modeling, which involves creating a mathematical representation of a physical entity (Figure 6).

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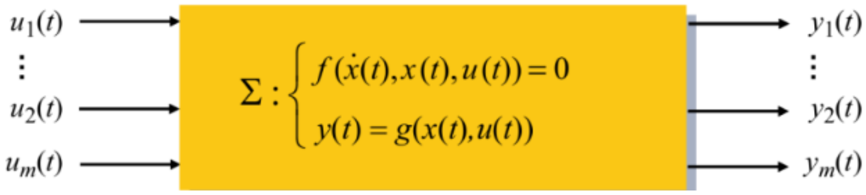

Figure 6. Representation of a calculation subsystem with input and output terminals.

Differential equations are fundamental for capturing the dynamics of physical systems. Ordinary Differential Equations (ODEs) are used for systems with a single independent variable, such as time, and are integral for modeling the trajectory of a moving object. For example, Newton's laws of motion are expressed as ODEs, such as the heat equation:

$$\frac{\partial u}{\partial t} = \alpha \nabla^2 u,$$

where u represents temperature and α is thermal diffusivity.

Partial Differential Equations (PDEs), on the other hand, are used for systems with multiple independent variables, such as time and space, and are essential for modeling complex physical phenomena like fluid flow or structural deformation. An example is the Navier-Stokes equations for fluid dynamics:

$$\rho \left(\frac{\partial u}{\partial t} + u \cdot \nabla u \right) = -\nabla p + \mu \nabla^2 u + f,$$

where u is velocity, p is pressure, and f represents external forces.

Data assimilation integrates real-time sensor data into the digital twin model to keep it accurate and up-to-date, with the Kalman filter being a key mathematical tool for this process. The Kalman filter is a recursive algorithm used for estimating the state of a linear dynamic system from a series of noisy measurements, employing state-space representations and linear algebra. The Kalman filter operates through two main steps: prediction, given by

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k,$$

and update, expressed as

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - H\hat{x}_{k|k-1} \right),$$

where A is the state transition matrix, B is the control input matrix, K_k is the Kalman gain, and H is the measurement matrix.

Optimization techniques are employed to improve system performance and efficiency by adjusting design variables. Linear Programming is a mathematical method for maximizing or minimizing a linear objective function subject to linear equality and inequality constraints, useful for applications such as minimizing operational costs while meeting production demands. Nonlinear Optimization deals with objective functions or constraints that are nonlinear and includes techniques such as gradient descent, Newton's method, and genetic algorithms. Multi-Objective Optimization addresses the challenge of

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optimizing multiple conflicting objectives, with algorithms like Pareto optimization and evolutionary algorithms being employed to balance performance and cost.

Predictive analytics involves forecasting future outcomes based on historical data, where machine learning algorithms are used for pattern recognition and prediction. Regression Analysis, a statistical method for modeling relationships between variables, includes techniques such as linear and polynomial regression for predicting equipment failure based on historical data. Classification Algorithms, including decision trees, support vector machines, and neural networks, categorize data into predefined classes for applications like classifying system states as normal or faulty. Time Series Analysis, such as ARIMA (AutoRegressive Integrated Moving Average), is employed for forecasting future trends based on past data.

Simulation models the behavior of systems under various conditions, with Monte Carlo Methods used to account for uncertainties and variability. Monte Carlo Simulation relies on probability theory and stochastic processes to estimate outcomes through random sampling and statistical modeling. For example, it can be used to estimate the risk of investment returns or the reliability of a system. The algorithm for Monte Carlo Simulation involves generating numerous scenarios to derive statistical distributions and make informed decisions, where $X_{i+1} = X_i + \Delta X$ represents changes in the system with ΔX being a random variable.

The mathematical foundations of DT are diverse and integral to their development and application. Differential equations are used for physical modeling, data assimilation is facilitated by Kalman filters, optimization techniques improve system performance, and machine learning algorithms provide predictive capabilities. Simulation and Monte Carlo methods address uncertainties, supporting the advancement and application of digital twin technology across various industries and its accuracy validation (Figure 7).

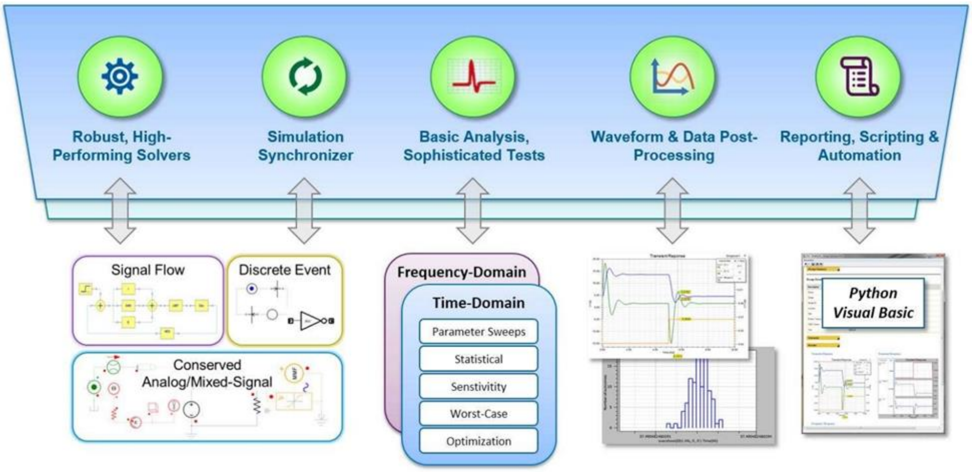

Figure 7. Digital twins' analysis features in ANSYS Twin Builder.

3. Practical implementation of digital twins in the automation system

At O. M. Beketov National University of Urban Economy in Kharkiv (Ukraine), which hosts a certified laboratory for electric drive and electric apparatus in collaboration with Schneider Electric, a research platform for investigation of electric drive system and electric transients was built [25–27]. This platform consists of power part (ATV320 and ATV930 frequency converters), controllers part (M241 series controller) and operator part that realize SCADA human-interface device (HMIST-U sensor panel, specialized software SoMachine, SoMove and Vijeo Designer by Schneider Electric). The picture of working place is shown on Figure 8.

The dispatching control systems of the electric drive of an induction motors (1 kW, 220/380 V, 1000 rpm by ABB) of the lifting and moving mechanisms of the bridge crane using Schneider Electric frequency converters and the study of the characteristics of these motors in transient modes of operation.

Figure 8. Electric drive SCADA system in university scientific laboratory.

The SoMachine Logic Builder software is intended for configuration and programming of Schneider Electric equipment, such as controllers, frequency converters, human-machine interface panels and other modules. In addition, projects configured in SoMachine allow diagnostics and maintenance of electric drives. The example of the developed SCADA project (controller testing part) is shown on Figure 9.

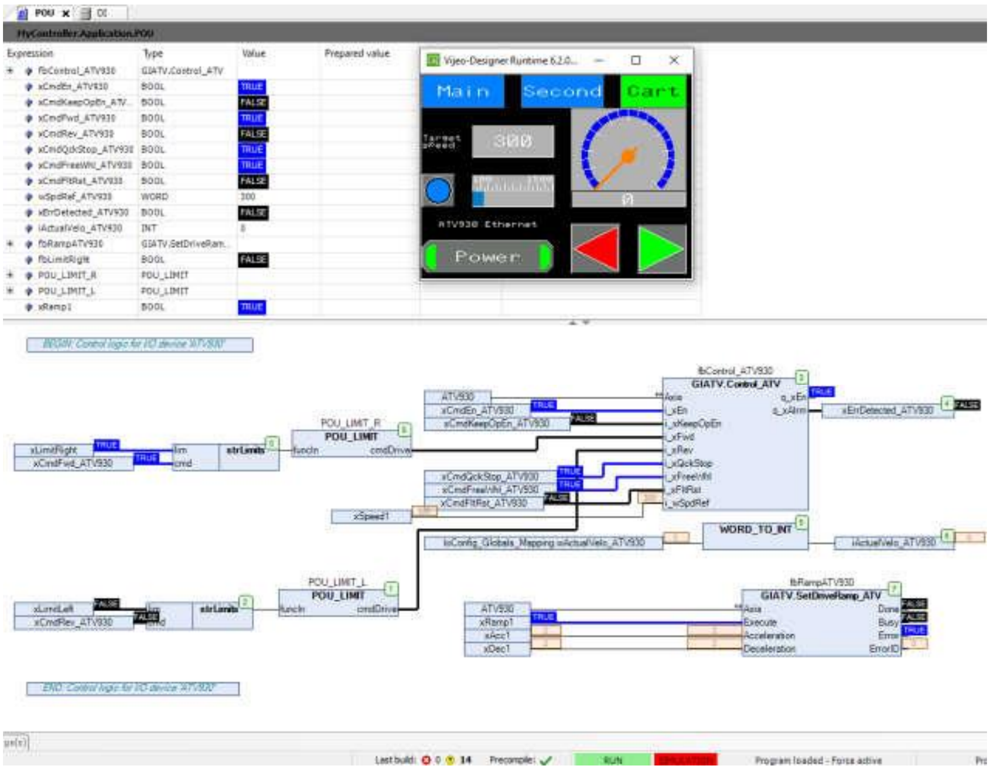

Figure 9. Simulation workspace of electric system in SoMachine by Schneider Electric.

From the point of view of the software that microprocessor devices operate, commands and signals are logical variables or numbers. These logical variables and numbers in real time must be simultaneously available to all devices of the control system, that is, located in the global data space or in the global storage. The use of this data is key in the organization of data transfer to the digital blasphemy and the implementation of the IoT technology. [28–30].

A digital twin can be exported and utilized on an IoT platform to forecast the remaining useful life of an electric motor for the purposes of predictive maintenance. This capability allows DT to be employed in academic laboratories for the simulation and replication of lab tasks, technical objects, and power energy systems.

Digital twins offer a range of significant benefits for a university's Electrical Energy Department. These benefits encompass educational, research, operational, and collaboration aspects, which collectively enhance the department's capabilities and resources. By simulating real-world electrical energy systems, students can visualize and interact with complex phenomena in a safe and controlled environment. This hands-on experience helps deepen their understanding of electrical engineering principles and system dynamics.

Implementing digital twins reduces the need for physical laboratory equipment, which can be expensive to acquire, maintain, and operate. By using virtual models, the department can simulate experiments and analyze systems without incurring the high costs of hardware and materials.

Digital twins enable students and researchers to conduct experiments in a risk-free virtual environment. This eliminates the potential dangers associated with high-voltage equipment, complex electrical circuits, or hazardous conditions, allowing for safe exploration of scenarios that would be dangerous or impractical in a physical lab setting. For instance, students can simulate fault conditions or emergency scenarios on power grids without any risk of equipment damage or personal injury.

At the scale of city power supply systems DT of electrical grids provide valuable insights and tools for improving efficiency, reliability, and sustainability. By creating a detailed virtual replica of the electrical infrastructure, operators can track the status of different components, such as transformers, substations, and distribution lines. This real-time visibility helps in identifying issues quickly and making informed decisions to ensure a stable and reliable power supply. For example, operators can monitor power flows, detect potential overloads, and adjust settings to prevent blackouts or service disruptions.

4. Conclusion

By leveraging ANSYS Twin Builder and ANSYS Digital Twin (DT), a highly precise digital model of an induction motor with an electric drive system has been developed. This advanced DT facilitates the exploration of real-world electric drive systems, enabling the enhancement of their performance and dependability. The presented model includes thermal analysis techniques to assess the operational characteristics of the induction motor, including the associated lifecycle components and predicted operational stability over time. Specifically, a reduced-order model (ROM) of the induction motor was created using ANSYS Ice Pack and integrated into ANSYS Twin Builder workspace to construct the coupling project with DT. Research demonstrates that employing DT technology not only streamlines the testing process for new electric drive designs but also significantly cuts both time and costs associated with physical prototyping. Furthermore, this approach supports virtual experimentation with various design alternatives, thereby minimizing risks and promoting more effective solutions for electric drive challenges.

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