Int j simul model 25 (2026) 1, 87-98
Original scientific paper

DIGITAL TWIN MODELLING VIA INTEGRATION OF SIMULATION AND DATA-DRIVEN METHODS

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Abstract

Digital twins – high-fidelity digital counterparts of physical assets – are increasingly used to solve real-world problems across industries. Building a high-quality digital twin requires an integrated stack spanning IoT, data processing, modelling & simulation, 3D visualisation, and networking, with the modelling layer pivotal. Yet widely adopted modelling practices remain limited. We propose a digital twin modelling method that combines simulation and data-driven modelling, selecting among three integration strategies by goal: (i) accuracy enhancement via calibration, assimilation, and hybridisation; (ii) execution efficiency via surrogate or reduced-order models; and (iii) decision optimisation via simulation-in-the-loop using learned response surfaces. We formalise selection criteria and workflows for each strategy and show their composition within a single methodology. A smart farm case study demonstrates improved predictive accuracy, reduced runtime, and support for operational optimisation, illustrating practical value for purpose-built digital twins.

(Received in November 2025, accepted in January 2026. This paper was with the author 1 week for 1 revision.)

Key Words: Digital Twin, Simulation Modelling, Data-Driven Modelling, Hybrid Modelling, Surrogate Modelling, Smart Farm

1. INTRODUCTION

A digital twin is defined as a twin of a physical object created in a virtual world, which can be used to predict and optimise objects in the real world [1]. These physical objects include people, products, and processes, and they can be expressed as digital replicas identical to physical objects by utilising information about the objects, such as operational data, maintenance data, a 3D CAD model, physical/operational laws, and system structure. This digital twin is one of the core technologies of the 4th industrial revolution in the era of digital transformation, and it can secure efficiency, safety, and economic feasibility by solving problems in the real world [2]. Digital twins are widely adopted across manufacturing, cities, defence, and healthcare, with strong engagement from industry and the public sector; in manufacturing, they are used to raise productivity and to detect or predict failures [3-6].

On the other hand, a digital twin cannot be built with a single technology but through the convergence of various ICTs, such as simulation, data analytics, machine learning, the Internet of Things (IoT), and a network [7]. In other words, it is difficult to achieve a true digital twin only by utilising each of the existing technologies, but it can be done through the synergy generated from the convergence of such technologies.

To build a digital twin, there are various considerations. For example, it is necessary to consider data collection and processing, digital twin modelling, 3D visualisation, and communication interface [8]. The core challenge in creating digital twins is building the digital twin model well. In other words, the following questions can be the key points to complete the digital twin: How is a physical entity represented as virtual behaviour and structure models of its digital twin? How many identities of a physical entity are represented as corresponding virtual models of its digital twin for conforming as much as exactly as possible to its real structure, behaviour, and personality [9]?

https://doi.org/10.2507/IJSIMM25-1-753

In this study, we focus on the digital twin modelling method among the various considerations regarding the digital twin. There are two main techniques for digital twin modelling: knowledge-based simulation modelling and data-based modelling [10]. Because each method has its strengths and weaknesses, it is necessary to use two methods in the right place, not just one method, to achieve high-quality digital twin modelling. Depending on the digital twin's purpose, it is very important to combine the two, and guidelines for this convergence method are needed for those who want to build a digital twin model.

Various studies on digital twin modelling have been conducted. For example, Schluse and Rossmann [11] and Zhang et al. [12] explain the overall concept and theory of the digital twin but do not present a specific and standardised methodology for the modelling. In addition, Zhang et al. [13] and Ivanov [14] deal with digital twin modelling, but their work can be seen as case studies on digital twin model construction through each domain analysis rather than methodology. Finally, Khalyasmaa et al. [15], García et al. [16], and Wu and Li [17] suggest the convergence of simulation and data-based machine learning but are limited to specific purposes and domains and do not provide a general theory for this.

Although researchers have conducted studies related to digital twin modelling, there is no standardised modelling methodology for it. In addition, it is important to complement the use of the two modelling methods mentioned above, which are necessary for building a digital twin model, but no specific guidelines have been presented for this. Therefore, in this paper, we suggest digital twin modelling methods that combine knowledge-based simulation modelling and data-based modelling techniques.

We organise the remainder of the paper as follows. In Section 2, we discuss background knowledge about the digital twin and its modelling method. Then, in section 3, we propose a digital twin modelling method. In Section 4, we present a case study that applies the proposed method to the smart farm. Finally, in section 5, we present our conclusions.

2. PRELIMINARIES

In this chapter, before examining the proposed methodology, we will look at the maturity spectrum of the digital twin model and the method of building the digital twin model in general.

2.1 Utilisations of digital twin

Regarding the maturity level of the digital twin, the three-stage model of digital twin technology Gartner [18] proposed is often mentioned. This is a step classified according to the level of realisation of the digital twin. Depending on the target, scope, and purpose of the digital twin, the level of the model to be used can be determined. First, the most basic step is simply to copy a physical object's shape. The second step is to monitor the real world in real time, and the third step is to predict and optimise the real world through control, analysis, and simulation [9]. That is, after one replicates one real-world object in a virtual world, prediction and optimisation are generally limited to that model. To overcome these limitations, [11] conducted a conceptual study that expanded the spectrum of the digital twin. As a fourth step, they propose a concept of interaction between heterogeneous digital twins through networks and interfaces rather than being limited to one system. Also, in the fifth step, organically connected digital twins are expanded to the level of autonomous operations and maintenance [12]. To date, there has been no case of building a digital twin at this stage, and this can be seen as the end point at which the digital twin must arrive.

2.2 Modelling of digital twins

Digital twin models can generally be used for analysis, prediction, and optimisation of real systems. One of the core technologies of the digital twin is how to create a digital twin model according to the purpose of use. In general, recent studies have dealt with the conceptual framework of digital twin technology or its practical application in real domains [13, 14], but there is a lack of technical discussion on how to create a digital twin model, which is a key element. In other words, because the domain to be applied and its purpose and level are diverse, case studies form the mainstream, and a standardised modelling methodology is not defined. Therefore, it is necessary to develop a model-construction method suitable for the purpose of utilisation by considering the availability and sufficiency of knowledge of and data regarding the physical object to create a digital twin model. To develop a digital twin model, a means to describe the properties, processes, and dynamics of the actual object properly is required. In addition, although the model's level of abstraction may vary depending on the purpose, a high-fidelity, high-resolution model is generally required to realise the potential of the digital twin concept.

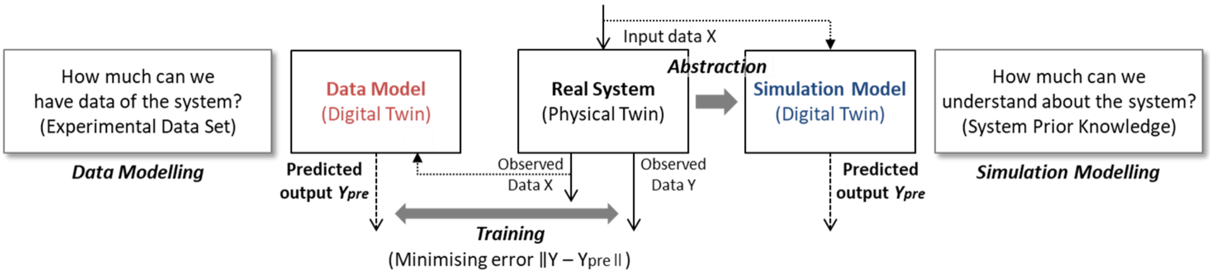


Figure 1: Two modelling methods: data modelling and simulation modelling.

As mentioned earlier, these models can be created through traditional knowledge-based simulation modelling or a data-based modelling method, as Fig. 1 shows. First, simulation modelling is a theory-based approach based on abstraction of the system using prior knowledge (physical/operational laws), which is generally used when sufficient information related to the target system can be secured [19]. It can clearly represent the causality between a set of inputs and corresponding outputs. Second, data modelling is based on analysing the data from a system, in particular finding connections between the system state variables without explicit knowledge of the system behaviour, which is mainly used when there is sufficient data that can be collected through the operation of the target object or when it is necessary to calculate the model's execution result in real time [20]. These two methods can be used individually in the development of a digital twin model, but there are cases in which they are not sufficient due to the limitations inherent in each method as follows.

First, in the case of simulation modelling, it is necessary to be able to secure specific knowledge about the target object's properties and operation characteristics. In addition, it is necessary to determine whether the implemented model has enough reliability to replace the actual object in terms of operational purposes [21, 22]. In contrast, in the case of data modelling, sufficient types and amounts of data necessary for model learning must be secured from the target object and causal relationship analysis to determine the cause of the problem is difficult. In addition, it is difficult to predict the future with a previously learned model if the system's configuration or operating rules change after learning [19].

For this reason, it is difficult to build a real object/system entirely as a digital twin model with one method, but this difficulty can be overcome by supplementing the limitations of each method with the advantages of other techniques. In particular, because data plays an important part in the digital twin model, a modelling method with a different perspective from the general simulation modelling method is required. In other words, depending on the reason for building the digital twin model, it is used to operate the two methods complementarily at the right time. Therefore, in this paper, we propose a new digital twin modelling methodology to expand the range of possible modelling for real objects through convergence and mutual complementation.

3. DIGITAL TWIN MODELLING METHODS

Digital twins can be widely used for multiple purposes across a product's / system's life cycle, targeting multiple layers of objects in a variety of industries. As mentioned above, various operation and modelling methods can be applied depending on the reason for building and utilising the digital twin. The first method is accurate system analysis and prediction, which is one of the most important purposes of the digital twin. In the pre-modelling stage, before the system is built, it is necessary to design a virtual model using existing knowledge, data, and ideas in the absence of a real system. At this time, the digital twin can be utilised for optimal design, reducing production/construction costs. On the other hand, in the post-modelling stage, after the product/system is built, it can be used to predict the future of the system by accurately modelling the physical twin that actually exists as a digital twin. In summary, by creating a digital twin model with high accuracy and precision, it is possible to design an object optimally for which a physical twin does not yet exist, and in the case of an object with a physical twin, it can be used for future prediction.

The second method is optimisation, in which the model is advanced while gradually optimising the digital twin model to operate the target product/system (physical twin) optimally or to utilise it for maintenance purposes, such as failure diagnosis and predictive maintenance.

The last method is to improve the model's performance for organic interoperation between the physical twins and digital twin models when it is necessary to operate them simultaneously for the purpose of optimal operation. In other words, real-time interoperation is secured by increasing execution speed via surrogate modelling, where parts of the already created digital twin are replaced with trained surrogates learned from the original model's input–output behaviour. In this chapter, as Fig. 2 shows, we present methods to apply the two digital twin modelling techniques according to each purpose.

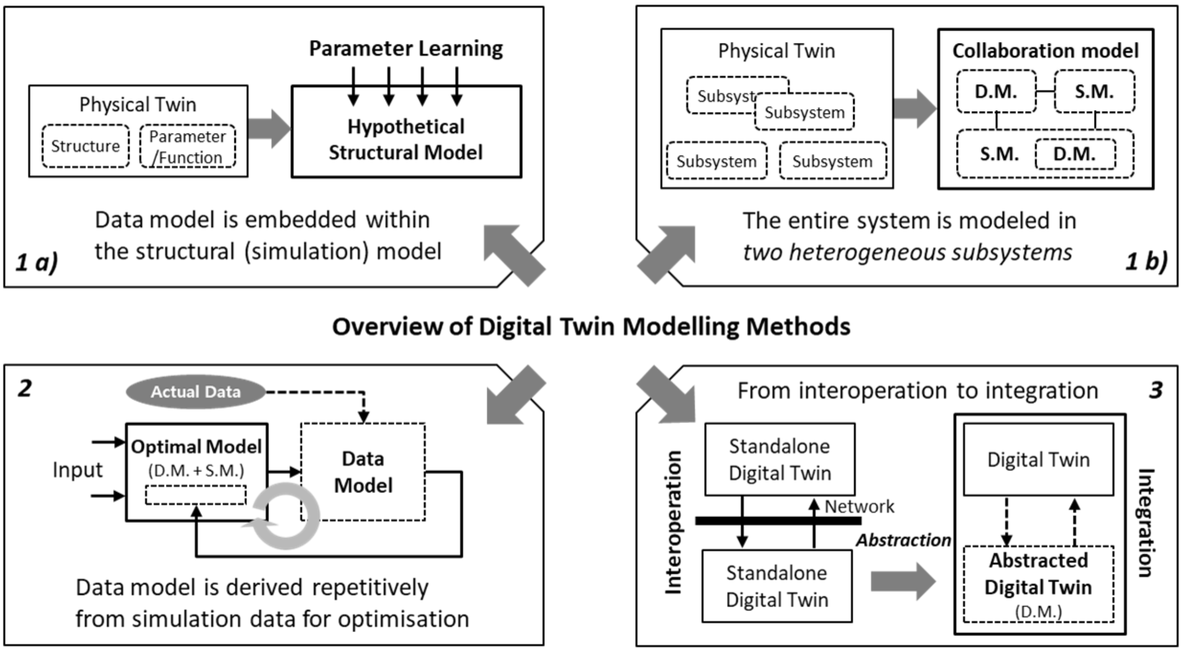


Figure 2: Proposed digital twin modelling methodology.

3.1 Prediction accuracy

To increase the digital twin's prediction accuracy, simulation modelling and data modelling must be used in the right place. At this time, the specific modelling method may vary depending on the level of abstraction of the target system for which the digital twin model is to be built. That is, it can be divided into a case in which the target system to be modelled can be separated into detailed components (subsystems) and a case in which it is difficult to separate it completely into its components. According to this, modelling methods can be classified. The upper part of Fig. 2 shows these two cases.

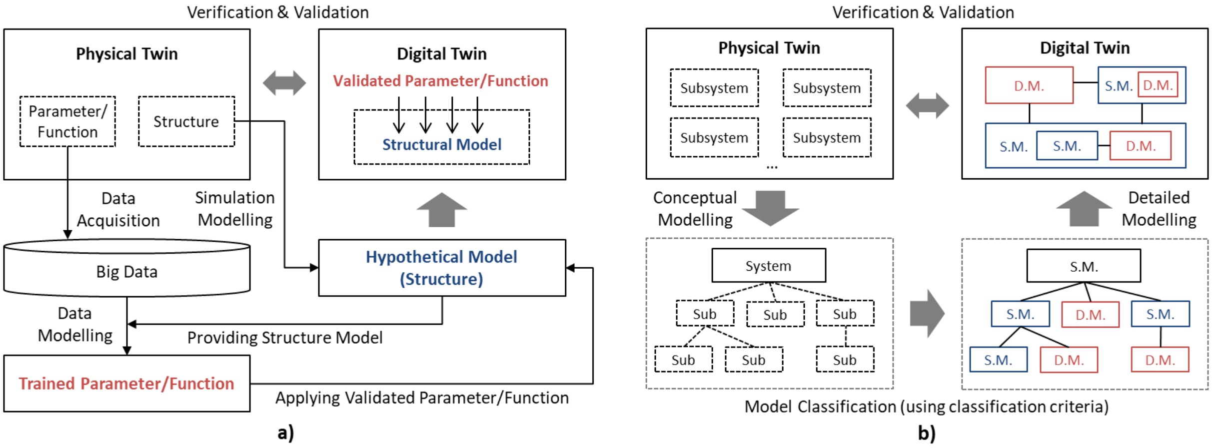


Figure 3: Two modelling methods for prediction accuracy.

The first case occurs when it is difficult to separate the system completely into component units. In this case, modelling is possible by dividing the structural model that forms the skeleton of the system and the parameters/functions that determine specific values. It can be seen as a kind of system identification [23]. This is done by embedding the trained data model that determines the parameters/functions in the system's structural model [24]. In this case, as Fig. 3 a shows, a hypothetical model is first established for modelling the target system, and its validation problem can be solved through data modelling. Specifically, the hypothetical model of the system is modelled using models such as physical equations and cellular automata, and the parameters and transition functions required for the hypothetical model are learned using big data obtained from observation/operation of real systems and elements of machine learning, such as artificial neural networks [25]. At this time, the entire model can be completed by applying the learned and verified parameters and transfer functions to the hypothetical model, which is the skeleton of the model. Through this, it is possible to solve the validation problem of simulation modelling and the limitation of structural change of data modelling simultaneously [26].

The second case occurs when the physical object to be created as a digital twin model can be modularly divided into its components. In this case, the entire system can be modelled as two types of heterogeneous subsystems, as the right-hand picture in Fig. 2 shows. In other words, each independent but compatible model is hierarchically connected with each role to form one whole system [20]. As the complexity of the physical twin to be modelled increases, the scale of these subcomponents increases, and accordingly, there are many cases in which it is not easy to model all the components with only one method. To this end, as Fig. 3 b shows, the first step is to divide the entire system into subsystems through conceptual modelling. Each subsystem is hierarchically structured, and vertical/horizontal two-dimensional separation is possible. For models separated in this way, it is possible to determine in what way they are modelled, based on model classification criteria. This classification criterion is the data/knowledge acquisition level of the physical twin, depending on whether it is a whitebox component whose internal operation principle is known or a black-box component whose internal operation principle is unknown, but the component's data can be acquired, and the modelling method can be determined. If data and knowledge acquisition levels are sufficient, they can be classified based on the fidelity or efficiency criteria required for modelling. For example, simulation models are available when high fidelity and relatively low efficiency. Conversely, data models are available with relatively low fidelity and high efficiency [20]. Components developed in this way can be modelled in detail by exploration formalism for each method and can be connected by mutually defined coupling relationships. At this time, to integrate and implement these models, an interface needs to be defined for interactions between the two heterogeneous model types.

3.2 Optimisation

The next step is to optimise the digital twin model progressively for optimal operation. In other words, the existing digital twin model created through the complementary use of the two methods can be optimised with data modelling through data acquisition and used for optimal operation in real time. To this end, as Fig. 4 a shows, simulation data is obtained through repeated execution of the digital twin model created using the previous method. An optimal data model can also be obtained through data modelling using actual data acquired from the physical twin. Then, by updating the coefficients or parameters trained through this data model and applying them to the existing digital twin model, the model can be continuously developed by acquiring the optimal operating conditions [19].

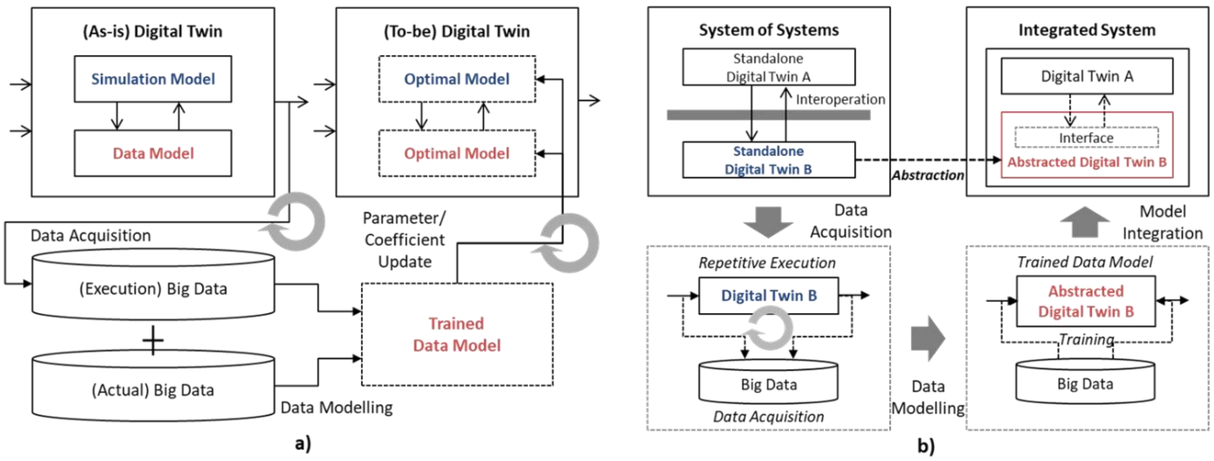


Figure 4: Cooperation for optimal operation and execution performance.

3.3 Execution performance

The last method is to increase the model's execution performance by lightening the model for real-time interoperation between digital twins or between the physical twin and the digital twin. Fig. 4 b is a case in which a system of systems between digital twins is established. At this time, it can be communicated through a network using interoperation middleware. In such cases, real-time operation may not be easy due to network overhead and poor performance of the digital twin model. To solve the problem, the input/output data can be obtained by independently repeatedly executing one of the digital twins first. After these data are pre-processed, a new surrogate model can be acquired through data modelling. Finally, it can be integrated locally through interface models to other digital twins (or physical twins).

This process can be seen as surrogate modelling, a kind of model abstraction process that makes a model of a model [27]. At this time, the data model is used not to express a part that the simulation model cannot express but to utilise the advantage of being able to execute more quickly than the simulation model [28, 29]. In other words, the part that the simulation model was previously responsible for in the entire model was modelled again through the data modelling method to improve speed. The model's accuracy is thus kept close to that of the previous model, the network overhead is eliminated, and the speed is much faster when the model is lightened.

4. APPLICATIONS

4.1 Overview of smart farm

In this chapter, we apply the proposed method to the digital twin construction of a smart farm. A smart farm uses ICT (e.g., IoT, drones, AI) to manage production, improving yield and quality while reducing labour [30]. Key variables – temperature, humidity, light, and soil – are measured and analysed for closed-loop control to maintain optimal conditions [31]. The concept extends across the agri-food chain, enhancing productivity, efficiency, and quality from cultivation through distribution and consumption [32]. Given the system's complexity and many interacting factors, smart farm digital twins benefit from the complementary use of simulation and data modelling, selected according to the analysis purpose [33].

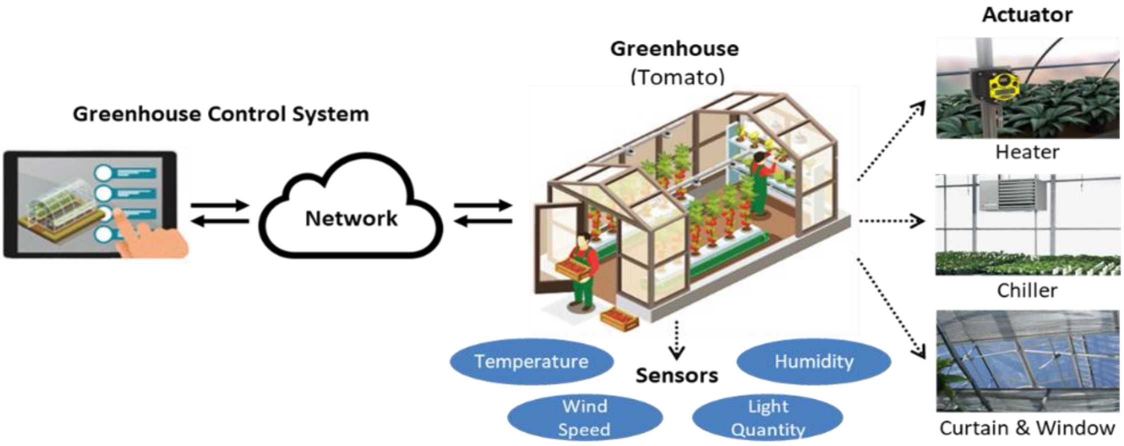


Figure 5: Overview of smart farm.

In this paper, digital twin modelling is performed for a simple greenhouse control system among various types of smart farms. The target greenhouse for modelling in this paper is a greenhouse that grows tomatoes as shown in Fig. 5, has a size of 2700 m^2, and has a control system that can remotely and automatically control windows, heaters, and curtains. To build its digital twin model, the system can be largely divided into human, plant, actuator, sensor, and outdoor environment. Sensors can measure temperature, humidity, CO_2, rainfall, wind speed, and light density, and actuators can operate air conditioners, windows, and curtains. In this case study, data measured by various sensors in an actual greenhouse for 3 months are used for modelling.

4.2 Detailed digital twin modelling

The digital twin model of the greenhouse can be modelled in various ways depending on the purpose. In other words, depending on whether the purpose is (1) predicting productivity (internal temperature), (2) optimising the controller for optimal cultivation conditions, or (3) improving execution speed for real-time interoperation, the methods proposed above can be appropriately applied. Fig. 6 shows the overall concept of applying each modelling method based on the purpose of building a digital twin of a smart farm. The first of these is the most basic plant modelling method for predicting the internal temperature of smart farm plants.

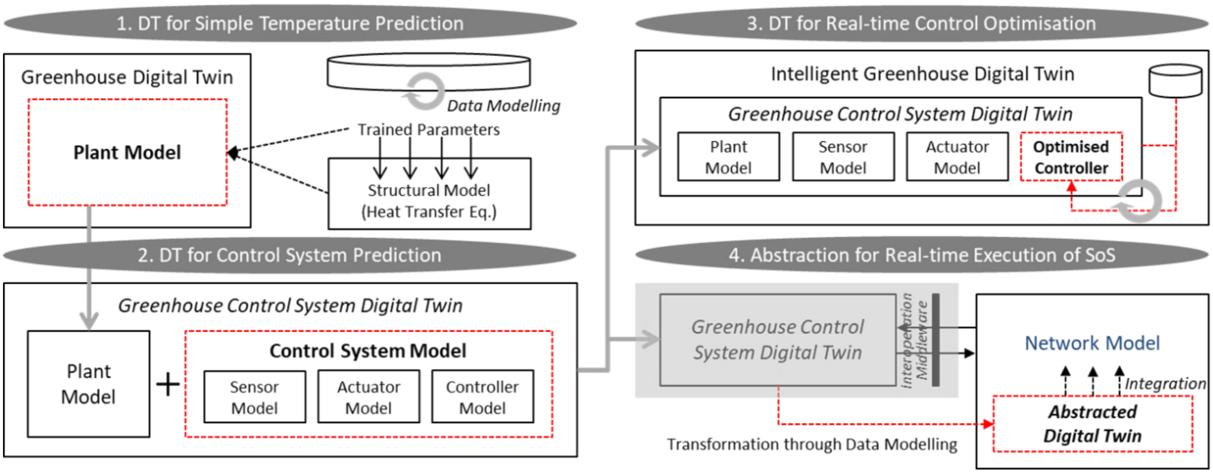


Figure 6: Digital twin modelling of a smart farm based on purposes.

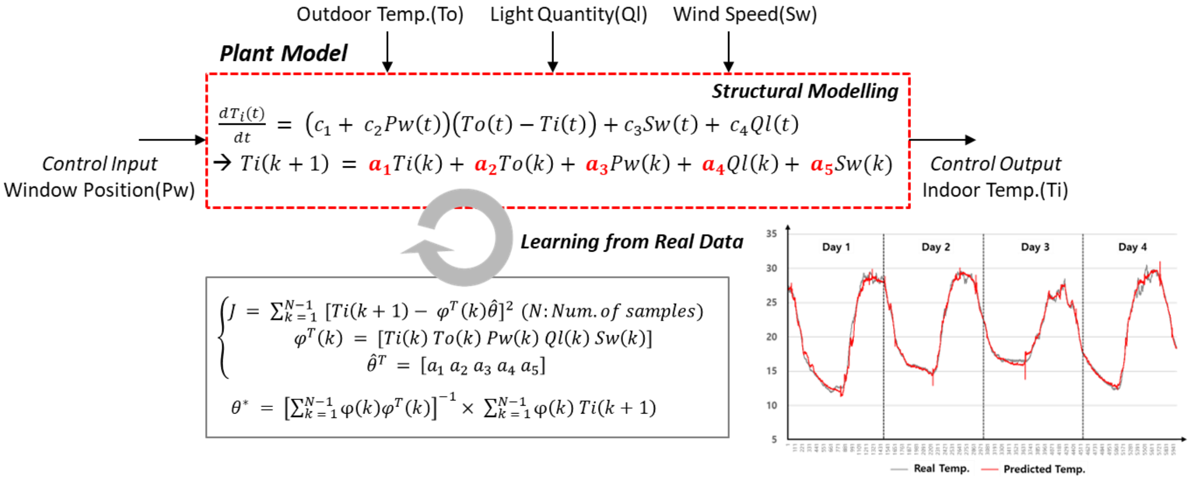


Figure 7: Modelling 1 – Digital twin for plant temperature prediction.

As Fig. 7 shows, the structural part of the plant model can be modelled using related physical laws. At this time, the structural model can be derived from the energy balance for the temperature equation and the water mass balance for the hygrometry equation. In this paper, we only consider the temperature model. The temperature model can be converted to a discrete model, which is a mathematical model with 5 coefficients. That is, this process is a kind of system identification process that identifies the dynamics of a system as a mathematical model using input and output data of an actual system. These coefficients are learned through the off-line least squares method using the acquired real data, as Fig. 7 shows. A simple greenhouse plant model can be completed by utilising physical knowledge and actual data. In other words, it can be seen that a validated model can be secured by learning using actual greenhouse data, and the model's performance can be checked using indicators such as root-mean-square error (*RMSE*). As the *RMSE* value of 1.82 in Table I indicates, it is possible to predict the temperature inside the plant with high accuracy.

Table I: Experimental results using digital twin models.

Type	**Modelling 1**	**Modelling 2**	**Modelling 3**	**Modelling 4**
RMSE	1.82 (plant)	2.86 (control system)	2.51 (control system)	2.66 (abstracted)

Next, as Fig. 8 shows, a digital twin model is built following the modelling method described above to predict not only the plant but also the entire greenhouse system, including the control system. To do so, the entire system is divided into subsystems for each element, and each model is classified as a simulation model or a data model, based on the classification criteria. Then, each of the classified subsystems is modelled in an appropriate way. At this time, the cooperative model modelled above is utilised for the plant model. In addition, the control system includes the window, heater, chiller, etc., which are essential elements for controlling the temperature and humidity inside the greenhouse. In this paper, only the window control part is considered, and the *P*-band concept for proportional control is applied as a control model. The *P*-band is a type of proportional parameter that regulates the window's opening angle in response to an excess of desirable temperature; the proportional gain constant (*Kp*), the general proportional parameter, is the reciprocal of the difference between the set point and the measured point [19].

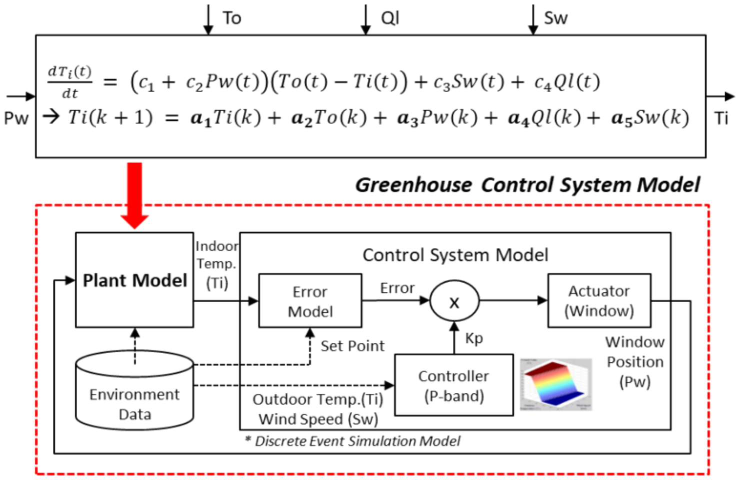


Figure 8: Modelling 2 – Digital twin for control system prediction.

In this case study, this overall control system is modelled using the discrete event system specification [21]. Finally, it is possible to obtain the overall greenhouse control system model by integrating the control system modelled using this formalism and the plant model previously created in the cooperative method. Using this, it is possible to predict the temperature after applying the control system and to predict the temperature inside the plant. As Table I shows, the prediction result using this model is *RMSE* 2.86.

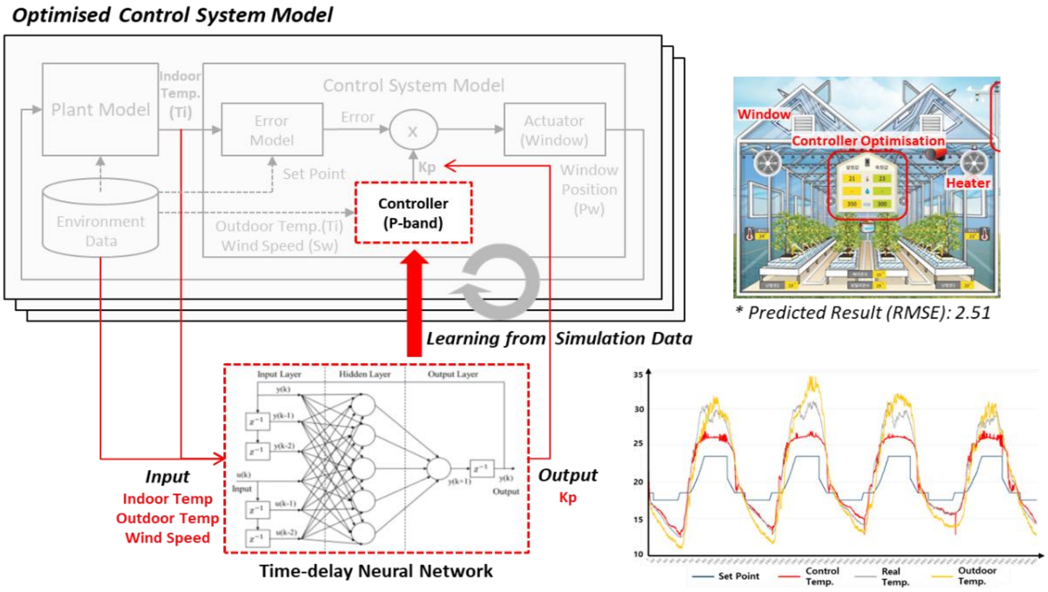
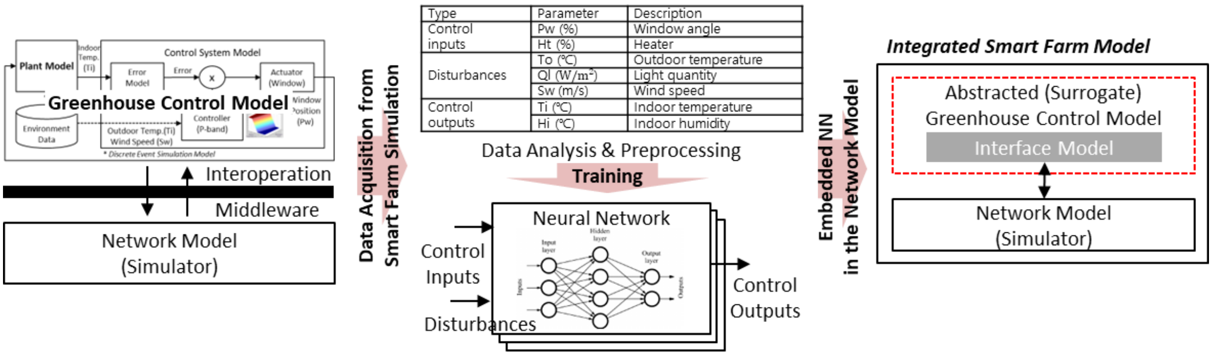


Figure 9: Modelling 3 – Digital twin for control system optimisation.

The third one is to gradually optimise the greenhouse control system to obtain optimal growing conditions. In other words, the simulation data for the internal temperature obtained through repetitive execution of the greenhouse model created through the previous collaborative modelling and the actual data, such as the external temperature and wind speed, obtained from the physical twin are all utilised. Using these data as training data, a time-delay neural network is trained, as Fig. 9 shows, for time series prediction. At this time, input values, such as indoor temperature, outdoor temperature, and wind speed, are used, and the optimised *Kp*' value is used as an output. Then, the optimal *Kp*' value is predicted in advance with the learned model, and this value is applied (updated) to the *P*-band in real time. In other words, by periodically applying this method, the optimal operating conditions of the greenhouse can be obtained and the model can be continuously developed. The graph in Fig. 9 shows the resulting controller optimisation, and it can be confirmed that the performance has increased to *RMSE* 2.51, compared to 2.86 before optimisation.



Type	Parameter	Description
Control inputs	Pw (%)	Window angle
	Ht (%)	Heater
Disturbances	To (℃)	Outdoor temperature
	Ql (W/m^2)	Light quantity
	Sw (m/s)	Wind speed
Control outputs	Ti (℃)	Indoor temperature
	Hi (℃)	Indoor humidity

Figure 10: Modelling 4 – Digital twin for real-time execution of smart farm system.

Finally, as Fig. 10 shows, the execution speed is increased by lightening the digital twin model to enable real-time interoperation between digital twins. When the greenhouse control system digital twin created above is driven through the network, the interoperation between this model and the network digital twin (or physical twin) is required. At this time, interoperation of the two standalone models is the main cause of time-consuming problems due to network communication overhead, and it makes real-time operation difficult. For this reason, by transforming the previously created greenhouse control system model and integrating it into the existing network model without using interoperation infrastructure, execution performance is maximised while ensuring accuracy. At this time, the model transformation consists of acquiring data through the operation (simulation) of the digital twin, analysing and preprocessing it, learning a neural network model, and embedding the neural network into the network model, as Fig. 10 shows. As a result, as Table I shows, the *RMSE* is 2.66; that is, the accuracy shows an error of about 6 %, but the execution performance increases by about 3 times, making it easy to operate in real time through model integration.

5. CONCLUSION

Despite the growing interest in digital twins, theoretical studies on digital twins are not yet mature. In particular, studies related to modelling methods, which can be regarded as one of the most important aspects of digital twins, need to be standardised and advanced. To create a digital twin model with a high degree of completion according to the purpose, it is necessary to utilise not only the existing traditional simulation modelling techniques properly but also data modelling through models obtained from original system. Therefore, in this paper, we proposed a digital twin modelling method that utilises two modelling techniques in one of three ways, depending on the purpose of constructing a digital twin. Then, by applying the proposed method, we conducted digital twin modelling for the smart farm. We were able to obtain the desired results by modelling the digital twin by applying an appropriate method according to each purpose of the model construction. Going forward, we will develop a modelling environment that implements the proposed method and a hybrid-simulation algorithm for the simultaneous analysis of heterogeneous models. We will also build an integrated digital twin environment with databases and interoperation interfaces for real-time data collection. These efforts aim to lower barriers to digital twin development and enable application across diverse domains.

ACKNOWLEDGEMENT

This study was supported by the Research Program funded by the SeoulTech (Seoul National University of Science and Technology).

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