Digital Twin Simulation Modeling Process with System Dynamics: An application to Naval ship operation

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Abstract

Digital twin (DT) has been around for many years, but there is no widely accepted standardized tool or method. In this study, system dynamics was proposed as a tool that can be integrated into multi-scale, multi-physics, and multi-disciplinary, which are continuously becoming issues in the DT field. Various heterogeneous data from multiple protocols or platforms could be integrated into one model. Through the five-step model building process, it was possible to integrate the theories and various models studied in the past. In this study, *the operation and maintenance system of ROK Naval ships* is implemented as a proposed method. Various physics, scales, and disciplines such as failures of ships, maintenance ability of repair shops and schedule pressure of mechanics were reflected. It was possible to observe non-intuitive correlations and potential problems caused by the latent effect of the high-fidelity DT model. The proposed method is also capable of updating through continuous data calibration or real-time interworking with external statistical analysis tools.

Introduction

Although widely used statistical and simulation models are excellent methods for data analysis, they have limitations in analyzing the complex real world. Statistical analysis can build high-fidelity models through calibration using big data, but it is difficult to implement a wide range of models (Richardson, 2015). This is because, as the model becomes more complex, programming becomes more difficult, and excessive time is consumed for analytical calculations. Simulation can model and analyze a wide world based on real data and theories. Although these models have advantages in verification, validation and optimization aspects, they have limitations in distribution assumptions or are not easy to apply during simulation run-time (Liu et al., 2021). Consider analyzing the logistics supply chain. The models implement a large-scale logistics system that not only reflects the various processes of SCM, but also considers precise demand patterns and raw material supply conditions. In simulation-based analysis, it is possible to build, verify, and optimize the model of the entire SCM, but it is difficult to include detailed parts such as failure of logistics equipment such as conveyor, palletizer, and folk lift. Their failures can become a bottleneck and affect the entire SCM, but in general, in the simulation model, these accidents are reflected as random event occurrences based on statistical theory. e.g., it is assumed that the failure of conveyor occurs randomly in a Normal (5, 10). On the other hand, using a statistical model, it is possible to analyze the failures of logistics equipment in a highly realistic way using big data. However, if the SCM is extended to a wide range, the complexity becomes too large, making it very difficult to build a model. Digital twin (DT) can simulate a wide world with high fidelity. DT is not a term referring to a specific technology. It is an idea that simulates the fusion of many existing cutting-edge technologies. It becomes a replica of reality by implementing the real world as closely as possible and calibrating it with data. It was originally proposed as a concept to support decision-making in the design phase of a product (Grieves and Vickers, 2017), but it is being used as an analysis tool of the total life cycle (Tao et al., 2019). The use of DT has the advantage of being able to understand anomalous events or unknown phenomena (Tao et al., 2018), but two major issues have not been established in academia. First, it is difficult to integrate multi-scale, multi-physics, and interfaces. DT studies should integrate models across lifecycle stages, taking into account various levels of detail and all relevant disciplines (Boschert and Rosen, 2016). There are 4 phases (design, manufacturing, service, retire) in the total life of a product (Liu et al., 2021). The units of various influence factors such as people, equipment, and systems are all different. It is difficult to build an integrated model considering their interfaces and protocols during the total lifecycle. Second, due to integration difficulties, a standardized process widely used for DT modeling has not yet been established. Existing DT studies utilize tools that are easy to implement for each phase of the total lifecycle. Many types of tools such as Predix, ANSYS, Bluemix, and MindSphere are being used. Most of the past DT studies have only integrated these multiple models into simple input/output (Liu et al., 2021). Therefore, there is a need to establish a standardized process that can fundamentally solve the mutual influence of different disciplines, time and space, and different formats and protocols. As a method to solve the two problems, this study proposes the construction of a digital twin using system dynamics (SD). In SD, it is possible to implement a complex world with a feedback loop composed of root causes (Sterman, 2010). Multiple data scales of heterogeneous physics existing on various platforms can be integrated, and multiple time horizons can be controlled, making it easy to build an integrated model. The latest SD tools have dramatically increased the reality by overcoming the limitations of traditional simulation models such as distributional assumptions, and a method to analyze the system model analytically is also provided. In particular, it is possible to support WinBurg-based MCMC in the system dynamics model, and to support interworking with programming languages R and Python. Application during run-time became possible, and data calibration became easy, resulting in very high fidelity (Richardson, 2015). In other words, if a DT model is built using SD, data of different formats and protocols and multi-disciplinary interface support are possible. Since SD models for each phase of the total life have already been studied a lot, it is possible to build a DT model by integrating them. Therefore, in this study, we propose to construct a DT model using SD. The proposed method is applied to *the operation and maintenance system of ROK Naval ships.* This system is the service phase of its total life. It is often known that the implementation of the service phase is the most difficult. This is because the service target is decentralized and it is difficult to consider all utilization in various environments (reliability, convenience, real-time operation status, maintenance strategy, etc.). Through the model building process proposed in this study, the process of integrating multi-scales and multi-disciplinary of multi-physics is confirmed, and anomalous events or unknown latent effects are identified. The remainder of this paper consists of six sections. The title of each section (Fig. 1) is the DT construction process using SD we propose. After selecting the target system, we explore and analyze the root causes. Various methods such as statistical modeling (B-spline, Bayesian estimation, phase type distribution fitting, etc.) and simulation are applied for analysis (Chapter 2). The dynamic variables related to the analyzed root causes are implemented as a system dynamics model (Chapter 3). The models built in Chapter 3 are applied as one module constituting the integrated model. In Chapter 4, the model is integrated and validated according to the causal relationship between modules. Simulate and analyze the integrated DT model to identify potential problems and latent effects (Chapter 5). Chapter 6 summarizes the results and limitations of the study and suggests future research directions.

Root cause exploration and analysis

The target system of this study is the operation and maintenance system of ROK Naval ships. Finding out what elements are included in the system is important in determining root causes. Brain storming or mind-map can be used. This process requires expert opinion. This is because it is necessary to determine the root causes by identifying the relationships among various influencing factors included in the system (Section 2.1). Root causes are analyzed using statistical models such as Bayesian inference, phase-type distribution, linear/multi regression, SD simulation models, existing theories about human work speed, and survey results (Section 2.2).

2.1. Root cause exploration

In addition to mind maps, you can use other methods such as brainstorming. These methods generally classify associative words hierarchically, but the classification is not important here. The key is to think of associative (or related) elements and make connections. The root causes search result through the mind map of the Operation and Maintenance System for ROK Naval ships is shown in Fig. 2. Starting from the target system, the causal relationships of the associative elements are indicated by arrows. Among them, those that affect many factors (Failure Probability), those that affect the policy of the system (Maintenance policy), those that require a separate analysis independent of the system (Maintenance technology), and the academic theory (Schedule pressure) are root causes. It is necessary to reflect the expert's domain knowledge rather than the analyst's subjective judgment.

2.2. Root cause analysis

This section introduces only the outline of the root causes in Fig. 2. For details of the analysis, refer to the following studies. Failure probability (Moon and Choi, 2021; Choi and Moon, 2022), Maintenance policy (Choi et al., 2020; 2021; Park et al., 2021), Maintenance technology (Choi and Moon, 2021), Schedule pressure (Oliva and Sterman, 2001). Failure probability is a root cause that affects many other factors. ROK Naval ships are maintained at regular intervals based on MTBF (Mean time between failure) according to the recommendations of the equipment manufacturers. Nevertheless, failures continue to occur. Recently, many efforts have been made to find the failure pattern over the total life using actual failure data (Zammori et al., 2020; Wang and Yin., 2019; Dikis and Lazakis, 2019). The failure pattern over the total lifetime is called the failure function. Ship failures are divided into two categories. One is that even if the performance of the equipment is partially degraded, it is possible to perform the mission. The other is a failure that immediately fails and requires repair by returning to the home port. In this study, the first is called normal failure and the second is called critical failure. The two failure functions were estimated by hierarchical Bayesian inference (Moon and Choi, 2021), combining trend and probability (Choi and Moon, 2022), respectively. The failure function is not in the form of a constant straight line. In some cases, failures during the total life cycle occur frequently and vice versa. Therefore, the MTBF-based policy of maintenance at regular intervals is inefficient. Choi et al. (2020; 2021) derived an appropriate maintenance interval based on the failure function. Park et al., 2021 analyzed maintenance intervals based on the naval fleet's ship arrangement. A system dynamics model was implemented and analyzed for the phenomenon of queues occurring due to mission delay and maintenance work delay. The maintenance policy to which the failure function was applied was advantageous in terms of operability of ships and repair shops. Since maintenance is performed by humans, the efficiency may vary depending on the technology of the repair shop. Choi and Moon (2021) made Bayesian estimation of the change in equipment condition before and after maintenance. Results ROK Navy's repair shop was able to complete an average of about 74% of repairs. In other words, if there are 100 faulty locations, it means that 74 locations are completely repaired after planned maintenance and 26 locations are insufficiently maintained. On the other hand, Oliva and Sterman (2001) argued that the speed of work varies by 75˜125% depending on the workload. In this study, based on this, the variability of the maintenance amount performed by mechanics was given.

Root cause model design

System dynamics can simultaneously reflect multi-physics, multi-scale, multi-interaction and multi-disciplinary in the model. The units of elements reflected in the model vary. Multi-physics includes ships, spare parts, mechanics, age of ships, and multi-scale includes manpower, number of ships, spare parts, mechanics, etc. If a more specific model is built, the types are more diverse. In this chapter, the root causes analyzed in Chapter 2 are implemented as a system dynamics model. Each root cause model is used as a module of the integrated model. Modules are linked according to causality.

3.1. Failure function modules

The advantage of using the lookup function of System dynamics is that it can express an unusual distribution. By implementing the average and variance of the daily failure probability during the total life of the failure functions as a system dynamics model, the occurrence of failures during the total life can be simulated. Fig.3(a) and (b) are the average of daily normal / critical failure function, respectively. Modules were constructed as shown in Fig. 4 using the mean and variance of the estimated failure functions. The two failure functions and variance are implemented, and the input/output relationship is briefly shown. The physics at this stage is a number of malfunctioning spare parts or equipment. Both failure functions have the same scale. Critical failure should be classified into physics different from normal failure because it is repaired by arriving at the port immediately after failure. Critical failure and normal failure are separated through integration with other modules (section 4).

3.2. Add maintenance policy module

Ships are operated under the policy of performing planned maintenance (1.5 months) after a certain operational operation (4.5 months). In Section 3.1, the unit of model was number of failures. The unit for planning maintenance is the number of ships. Although their scale is different, they are easily integrated in system dynamics. The part marked in red in Fig. 5 is the maintenance policy module. Maintenance criterion determines the number of operating days of a ship. It may be set to a different date depending on the policy (In the case of Condition based maintenance (CBM), the maintenance time is determined based on the ship status. In CBM, this variable determines the number of flexible operating days). After 137 days or 138 days, the ship in the Battle field moves to the Repair shop. After 45 days of movement, the ship moves to the Battle field through Return to field. Fig.6(a) shows the relationship of ship movement. Although the two modules have different units, they interact and work at the same time. Fig.6(b) shows the change of failures according to the operation and maintenance of the ship. Failures accumulated from 137 to 138 days are repaired for 45 days. The total life of the ship is 31 years. Since operation and maintenance are repeated twice a year, there are exactly 62 peaks in Fig. 6(b). Through the merging of two modules with different units, it can be seen that the system dynamics supports multi-scale.

3.3. Add maintenance technology and schedule pressure module

It is difficult to complete the maintenance of a ship 100% perfectly. In other words, it is difficult to return to the same condition as new after maintenance. The repair shop's technical skills and natural aging are the reasons for this. Maintenance technology refers to this phenomenon. Choi and Moon (2021) estimated the technical level of Naval ship's repair shop by Bayesian inference. On average, it was repaired at a level of 74%. If maintenance is performed with 100 failures, 26 failures cannot be completely repaired and remain on the ship. On the other hand, Oliva and sterman (2001) studied that the speed of a person's work varies by 75˜125% depending on the workload. Mechanics can perform maintenance faster when there is a lot of work and more slowly when there is less work. The standard working day for the Navy is 8 hours. When they are busy, they can perform 10 hours' worth of maintenance (8*1.25). The disciplines were applied using system dynamics. The model in Fig. 7 includes disciplinary (schedule pressure) and maintenance technology (Effective of maintenance). Although the scales of all modules are different, building them into one model is not different from the process of building a system dynamics model in general.

Model integration and validation

The module building process in Section 3 includes the integration process. This is a process for establishing the interface relationship between modules. Based on this, the integrated model should set the same number of ships, mechanics, maintenance policy, etc. The method is the same as the add process in section 3, but the model becomes visually complex as shown in Fig. 8. The simulation result of the integrated model should be able to simulate the real result as it is. Therefore, validation through robustness or sensitivity tests in DT is more important. The implementation of the functions included in the modules of Section 3 utilized the lookup function of the system dynamics tool (Vensim). The purpose of this study is to show that multi-physics and multi-scale problems can be solved by using system dynamics. In the DT building process, these lookup functions can be designed to be continuously updated during the simulation process. This is because the latest tools support data calibration using MCMC (Markov chain monte carlo) and link with programming languages (python, R, etc.) or other analysis methods (analysis tools). For details, see Richardson (2015), Sücüllü, C., & Yücel (2014). The integrated model is shown in Fig. 8. Compared to the model in Section 3.3, it is visually more complex, but the model operation process is the same. The items additionally reflected in the model are as follows. The number of ships increased from 1 to 6. A virtual waiting space was applied because a queue may occur in the movement of the ship between the battle field and the repair shop. It was modified to handle normal failure and critical failure separately. And the night additional work of the mechanics was set to be possible up to 4 hours a day. The ages of the 6 ships are all different, and the ages of the actual naval fleet ships are applied. In the work of increasing the number of ships to 6, it is necessary to make sure that the priorities of entering the repair shop do not conflict, but it is not difficult. It should be noted that multi-physics support is possible. Although tangible and intangible physics such as ships, number of people, and manpower have their own scales, they interact with each other through causal relationships. Validation of some variables included in the DT model is shown in Fig. 9. All reflected variables must be checked one by one. All variables of the model reflected reality well.

Simulation, analysis and global optimization

Analyzing the simulation results of the DT model is the same as analyzing reality. Real variables are composed of complex causal relationships. In the DT model, many loops are created by the connection of modules. In the case of Fig. 8, there are about 230,000 loops. Humans cannot intuitively know these complex relationships. So, in reality, sometimes unexpected results can come out. This is due to the influence of variables that were not considered. Assume that the Naval operation period is relatively longer than the maintenance time. The longer the equipment run time, the more failures. As maintenance costs increase, total life cycle cost increases. This sequence may seem like a natural result. However, the simulation results show that the total life cycle cost is reduced. See section 5.1 for more details. In the DT model, it is possible to simulate latent effects or potential problems that occur due to the simultaneous influence of multiple modules and variables. By checking the simulation results, the relationship between cause and effect can be established. Examples are the relationship between the operating period of the ship and the total life cost, or the relationship between the number of mechanics and the failure probability of the ship. In this study, linear regression is simply used, but a high-precision method such as multi-regression may be applied if necessary (section 5.2). It is meaningful to perform optimization by integrating all the variables, but computation time constraints may occur. In this study, a rough optimization is performed using the equation calculation established by linear regression (section 5.2). Section 5.2 examines maintenance policies with the DT model. As shown in Table1, a total of 4 models are composed. In the current Naval policy, ships start maintenance 1.5 months after 4.5 months naval operation. However, to simulate advanced policies such as condition-based maintenance, it is assumed that normal failure means the condition of the ship. Normal failure limits the performance and worsens the condition of the ship. On the other hand, the repair period is not fixed at 1.5 months, but consider the situation in which the maintenance period can be terminated as soon as the repair is completed.

Table 1 4 Models

Model	Criteria for maintenance	Repair period
Model 1 (PFM_FRP)	? PFM : Period fixed maintenance	? FRP : Fixed repair period
Model 2 (PFM_NRP)	? PFM : Period fixed maintenance	? NRP : Non-fixed repair period
Model 3 (FFM_FRP)	? FFM : Failure rate fixed maintenance	? FRP : Fixed repair period

Model	Criteria for maintenance	Repair period
Model 4 (FFM_NRP)	? FFM : Failure rate fixed maintenance	? NRP : Non-fixed repair period

Model 1 is the current Navy policy. Model 4 is similar to Condition based maintenance (CBM). Perform maintenance according to the condition of the ship and start naval operation as soon as maintenance is completed. Models 2 and 3 are alternatives that can be used in the process of developing CBM from the current policy. Because the military is a conservative group, they tend to avoid innovative improvements. Models 2 and 3 can be used in this case.

5.1. Non-intuitive correlation

The DT model is composed of a complex causal relationship, and a latent effect occurs during the interface process between modules. A potential problem is sometimes found due to the latent effect. The correlation of simulation results included a potential problem. This is because the results showed that if the improved maintenance policy promoted by ROK Navy was continuously applied, the cost and the probability of mission failure would increase. Due to military security concerns, details cannot be disclosed. This was due to the limitations of human analytical ability. This section explains that non-intuitive results can be confirmed by using the DT model through an example.

Table 2 Correlation examples

Variable	Variable	Coefficient
Operation period	Mean number of critical failures	0.58
Operation period	The cost of spare parts during the total life cycle	-0.86

In Table 2, a large operation period means that there are many naval operations. That is, the degree of exposure to failure is large. The coefficient of both variables is 0.58. At this time, since many failures occur, the cost of spare parts will be larger during the total lifecycle. This is interpreted intuitively. However, the coefficient of operation period and cost of spare parts during the total lifecycle is -0.86. This can be found in the Navy's maintenance policy. In the current policy of 1.5 months maintenance after 4.5 months of operation, if the operation period is increased, the total number of preventive maintenances performed during the total lifecycle decreases. In other words, it is also interpreted to mean that the cost of spare parts used for preventive maintenance is higher than the cost of spare parts caused by critical failure during the total lifecycle. Even if the unit price of spare parts used for critical failure is much higher than the cost used for preventive maintenance. This may seem simple to interpret, but to naval policy makers, it is not. This is because the increase in total lifecycle cost caused by the increase in critical failure was taken for granted. When the correlation of all variables is checked, the more complex the relationship, the more difficult it is to interpret. However, the analysis results can be used as important. Among them, the interpretation that maintaining the current policy could lead to catastrophic results was also found. If the DT model is used, potential problems caused by the latent effect can be discovered only by correlation analysis.

5.2. Linear regression and optimization

If the results of DT simulations can be analyzed and optimized, the system can be improved. Each simulation result of the four models was linearly regressed. Compared to non-linear, it is easier to understand the relationship between variables. Depending on the purpose, multi-regression or other statistical methods may be applied. Fig. 10 shows the results of linear regression of operational availability (Ao) and probability of critical failure (Probability_CF). Their relationship is related to the reliability of the mission. This is because the success rate of the mission is determined depending on which policy is adopted after setting the target Ao. If Probability_CF is small at the target Ao line, it can be said that the policy has a high mission success rate. As shown in Fig. 10, in the case of PFM_NRP and FFM_NRP, Probability_CF is 0 at target Ao.

In the regression with a higher dimension, FFM_NRP had a lower Probability_CF at Ao. The relationship between PFM_FRP and FFM_FRP is noteworthy. FFM_FRP is the basis of CBM. Since the maintenance time is flexibly determined, normal failures accumulated in the ship can be effectively repaired. However, if FFM_FRP is applied, Probability_CF is higher than the current maintenance policy (PFM_FRP) in target Ao. In other words, it has the advantage of being able to effectively repair failures, but the probability of mission failure during naval operation is higher. If the navy pushes forward to apply CBM, it can be seen that not only FFM but also NRP should be promoted at the same time. In the case of this research model, 1.2 billion simulations were required for each model in order to confirm all the necessary scenarios in ROK Navy. In the performance of the computer used in the study (Intel Core i7 2.6Ghz, 16GB DDR4 RAM), about 5 seconds was consumed for one simulation. Linear regression can be used as a method to solve time-consuming problems in large-scale simulations such as DT. This is possible by constructing an optimization objective equation and performing arithmetic calculations using a linear regression equation between the independent variable and the dependent variables constituting the objective equation. The Navy needs a policy with high operational availability, low mission failure rate (probability of critical failure), and low total lifecycle cost. Expression (1) is equivalent to expressing their relationship. $\frac{\text{Operational availability}}{Probability\ of\ critical\ failure \times\ Life\ cycle\ cost}$ (1) It took about 16 minutes to check the optimization results of the models with the objective of Equation (1). The method using the linear regression equation has the advantage of being able to quickly check the rough results, although the accuracy will be lower than that of simulating all scenarios or calculating through non-linear relational equations.

Conclusion

Digital twin research has been started for many years, but there is no standardized tool or method recognized by the academic community. In this study, system dynamics was proposed as a tool that can solve integration problems such as multi-scale, multi-physics, and multi-disciplinary, which are continuously becoming issues in the digital twin field. By utilizing this, it was revealed that various heterogeneous data from various protocols or platforms can be integrated into one model. In addition, the five-step DT construction process was explained using actual data. Through the simulation results, it was confirmed that the potential problem caused by the latent effect can be found, and the method of optimizing it using the results is described in a rough way, which can contribute to the usability aspect. In this study, in order to explain the model building process using system dynamics, the update of variables is omitted (most statistical model-based modules are implemented with the lookup function). In actual DT simulation, real data is accumulated and run-time update of root causes is possible. Details on this can be found in Sücüllü & Yücel (2014) and Richardson (2015). In this study, only the service phase was implemented among the 4 phases of the total lifecycle, but design, manufacturing, and retire phases can all be added by using the module addition method described in this text. Since the system dynamics model for each phase of the total life has been studied a lot, the DT model can be completed by integrating them.

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