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Methodology To Prevent Local Optima And Improve Optimization Performance For Time-Cost Optimization Of Reinforcement-Learning Based Construction Schedule Simulation

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Abstract: The availability of PMT(Project Management Tool) in the market has been increasing rapidly in recent years and Significant advancements have been made for project managers to use for planning, monitoring, and control. Recently, studies applying the Reinforcement-Learning Based Construction Schedule Simulation algorithm for construction project process planning/management are increasing. When reinforcement learning is applied, the agent recognizes the current state and learns to select the action that maximizes the reward among selectable actions. However, if the action of global optimal points is not selected in simulation selection, the local optimal resource may receive continuous compensation (+), which may result in failure to reach the global optimal point. In addition, there is a limitation that the optimization time can be long as numerous iterations are required to reach the global optimal point. Therefore, this study presented a method to improve optimization performance by increasing the probability that a resource with high productivity and low unit cost is selected, preventing local optimization, and reducing the number of iterations required to reach the global optimal point. In the performance evaluation process, we demonstrated that this method leads to closer approximation to the optimal value with fewer iterations.

Key words: Time-Cost Optimization, Local Optima, Reinforcement-Learning Based Construction Schedule Simulation

1. INTRODUCTION

In recent years, the availability of Project Management Tools (PMT) in the market has experienced a rapid increase. Significantly, these tools have advanced to cater to the needs of project managers, offering enhanced capabilities for planning, monitoring, and control [1].

Among the diverse array of tools, the Reinforcement-Learning Based Construction Schedule Simulation algorithm has emerged as a potential game-changer for the field of construction project process planning and management. Consequently, research in this area has witnessed a notable surge

[2]. Reinforcement learning, known for its effectiveness in addressing management issues pertaining to resource allocation and activity sequencing, including time-saving scheduling and activity predecessor selection, has garnered considerable attention. However, in previous studies, project managers encountered challenges in using simulation techniques due to the substantial effort and knowledge required, along with the failure to consider on-site conditions in deriving productivity by equipment combinations and the lack of consideration for risk. [3] proposed a method for deriving productivity by equipment combinations using Discrete Event Simulation (DES), while [4] introduced a conceptual approach for optimizing construction project planning through the application of equipment combination derivation data and risk data. However, the study encountered a phenomenon of local optima during the process of utilizing simulation techniques based on the aforementioned productivity by equipment combinations data and risk data [3],[4]. Local optima refers to points in a problem space where a proposed solution is optimal within a neighborhood of points, but not necessarily optimal in the entire problem space. If the action of global optimal points is not selected in simulation selection, the local optimal resource may receive continuous compensation (+), which may result in failure to reach the global optimal point. We encountered the phenomenon of local optima during the process of selecting the optimal equipment combination for each activity, and devised a method to address this phenomenon. Therefore, this study presented a method to improve optimization performance by increasing the probability that equipment with high productivity and low unit cost is selected, preventing local optimization, and reducing the number of iterations required to reach the global optimal point.

2. CONSTRUCTION SCHEDULE SIMULATION IN THIS STUDY

This study utilized a construction schedule simulation created by conceptual approach based on reinforcement learning, utilizing information derived from productivity by equipment combination using DES, and risk data [3],[4],[5].

2.1. Conceptual approaches based on reinforcement learning

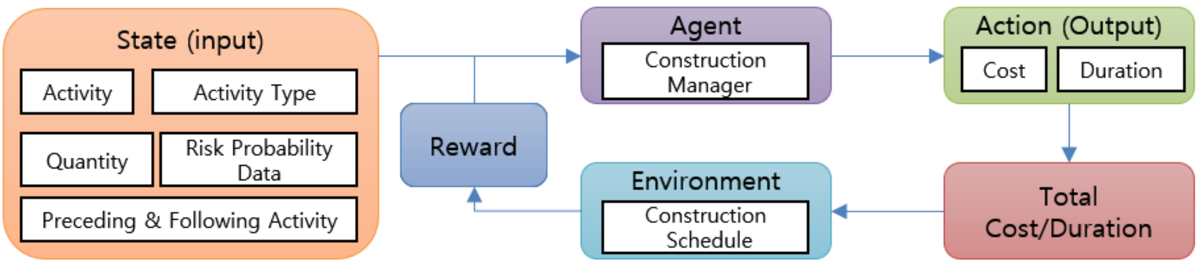

Figure 1. Conceptual Diagram of a Reinforcement Learning Based Construction Schedule Simulation

Reinforcement learning is a subset of artificial intelligence in which an Agent in a particular Environment recognizes the current State and takes Actions to maximize the Reward obtained from the environment. When these characteristics are applied to construction project planning, it can be represented as shown in Figure 1.

The agent selects actions to determine the cost and duration of the process, and by repeating these steps, the total duration and total cost of the entire construction schedule are determined. The agent learns in a manner that maximizes rewards by comparing the total duration and total cost with the objective duration and objective cost, and assigns rewards (+) or penalties (-) accordingly [4].

2.2. Derivation of Productivity by Equipment Combination using DES

To derive equipment combinations and productivity, the following process was conducted. Firstly, site observations were made, and the process was analyzed. Subsequently, DES-based process modeling and coding were performed. In this study, the 'Cyclone,' a DES-based optimal construction simulation methodology, was utilized [6]. Next, task durations were calculated based on the standard production capacity of construction equipment. Then, equipment combination and productivity data were generated through DES simulation, and unit costs were determined by applying price information.[3]

2.3. Risk Data

Risk data refers to information about various risks that may occur during the process execution, including types of risks and probability distributions of risks (severity of occurrence, severity distribution).

2.4. Utilizing Modified Adaptive Weight Approach (MAWA) function for multi-objective optimization

Construction scheduling simulation aims to optimize project planning within a constrained duration and at minimum cost, requiring consideration of both time and construction expenses. For this purpose, at least two objective functions are needed. To simultaneously optimize multiple objective functions, Multi-Objective Optimization is necessary. One commonly used method in Multi-Objective Optimization is the Weighted Sum Method, where weights are assigned to each objective function to transform them into a single objective function. The weighted sum method is intuitive and easy to interpret, as well as simple to code and apply. In this study, we applied the MAWA function, one of the weighting methods, by modifying it to suit the purpose of the fitness function. The results calculated through the fitness function are compared with target values and play a role in assigning rewards (+) or penalties (-) to the agent. Eq. (1) is the modified equation [7].

$$f(k) = \omega_t \frac{z_t^{max} - z_t(k) + \gamma}{z_t^{min} - z_t^{min}(k) + \gamma} + \omega_c \frac{z_c^{max} - z_c(k) + \gamma}{z_c^{min} - z_c^{min}(k) + \gamma} + \frac{z_t^{obj} - z_t}{z_t^{obj}} + \frac{z_c^{obj} - z_c}{z_c^{obj}} \quad (1)$$

3. PREVENTING LOCAL OPTIMA THROUGH INITIAL SELECTION PROBABILITY ADJUSTMENT

Figure 2. Diagram of Construction Schedule Simulation Model Learning Process in This Study

The construction schedule simulation utilized in this study guides the selection of optimal equipment combinations by randomly choosing equipment combinations for each construction activity and assigning rewards (+) or penalties (-) based on the productivity and cost information of the selected equipment combinations for the entire construction activities, as illustrated in the figure 2.

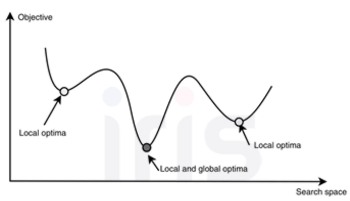

Figure 3. Local And Global Optima

If the optimal equipment combination fails to be selected due to unfortunate circumstances and local optimal combinations persistently chosen, it leads to a situation where these local optimal combinations receive continuous rewards, preventing the attainment of the global optimization point. To prevent such local optimization, the overall optimization can be induced by adjusting the probability of arbitrary selections on the simulation based on the relationship between productivity and cost of equipment combinations.

3.1. Utilization of Productivity and Unit Cost Based on Equipment Combinations Derived Through DES

To optimize the time-cost of construction scheduling, it is essential to select the optimal equipment combination that maximizes productivity while minimizing unit costs, considering the productivity and unit costs associated with the equipment combinations derived through DES. From this perspective, it can be seen that efficiency is maximized when productivity is high and unit costs are low. Therefore, the relationship between efficiency, productivity, and costs can be expressed as Equation (2) below.

$$\frac{Productivity[m^3/day]}{Unit\ Cost[KRW/m^3]} = Efficiency \tag{2}$$

3.2. Initial Selection Probability Adjustment for Highly Efficient Equipment Combinations

The manager adjusts the initial selection probability of equipment combinations with higher efficiency to be higher. Depending on the number of equipment combinations and the distribution of efficiency for each combination in the relevant trade, administrators can determine the increase in selection probability by setting the number of top efficiency equipment combinations and parameters such as the increase multiplier and ratio.

4. APPLICATION OF METHODOLOGY AND PERFORMANCE EVALUATION

In this study, a construction schedule sample and a statement sample were created for the application of the methodology aimed at preventing local optima through initial selection probability adjustment. This methodology was applied in the simulation with a target duration of 36 days and a target cost of 970,000,000 won. The simulation was conducted with iteration numbers set to 50, 150, and 300, each repeated five times. Additionally, the simulation was carried out under the same conditions without applying the methodology.

PL6	PL7	P_ID	mass	mass unit	total_cost_
흙깎기	토사	1E	8150	m3	1144
흙깎기	토사	2E	6815	m3	1144
흙깎기	토사	3E	5313	m3	1144
흙깎기	리핑암	5E	7505	m3	4894
흙깎기	리핑암	6E	8055	m3	4894
흙깎기	리핑암	7E	5408.5	m3	4894
흙운반	사토	1T	8150	m3	7647
흙운반	유용토운반	2T	6815	m3	14501
흙운반	유용토운반	3T	5313	m3	14501

Figure 4. Part Of A Statement Sample

PWBS Cod	PL6	PL7	P_ID	du	start	end	pre	suc
F1110111F	흙깎기	토사	1E	5	01-Aug-22	06-Aug-22	START	1T
F1110111F	흙깎기	토사	2E	6	04-Aug-22	10-Aug-22	START	2T
F1110111F	흙깎기	토사	3E	5	06-Aug-22	11-Aug-22	START	3T
F1110111F	흙깎기	리핑암	5E	6	13-Aug-22	19-Aug-22	START	5T
F1110111F	흙깎기	리핑암	6E	7	05-Aug-22	12-Aug-22	START	6T
F1110111F	흙깎기	리핑암	7E	6	22-Aug-22	28-Aug-22	1T	7T

Figure 5. Part Of A Construction Schedule Sample

Table 1. Total Duration And Total Cost At 50 Iterations

Iteration_50	Try-1	Try-2	Try-3	Try-4	Try-5
A_TD(day)	33	33	33	33	33
B_TD(day)	33	33	33	33	33
A_TC(won)	952393279	926786335	927942183	933889191	904719222
B_TC(won)	979181651	984827207	1012565230	1004605327	1008292380

Table 2. Total Duration And Total Cost At 150 Iterations

Iteration_150	Try-1	Try-2	Try-3	Try-4	Try-5
A_TD(day)	33	33	33	33	33
B_TD(day)	33	33	33	33	33
A_TC(won)	894755485	886770360	882674161	879304843	890496646
B_TC(won)	911091536	926980285	946870015	953130495	929414833

Table 3. Total Duration And Total Cost At 300 Iterations

Iteration_300	Try-1	Try-2	Try-3	Try-4	Try-5
A_TD(day)	33	33	33	33	33
B_TD(day)	33	33	33	33	33
A_TC(won)	891629796	895900065	874900414	889217371	884425552
B_TC(won)	913167791	911968907	895779208	914832777	923983231

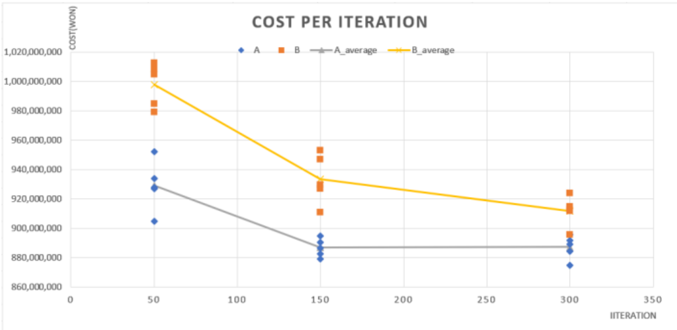

Figure 6. Cost Per Iteration

The three tables above represent the results of simulations based on the construction schedule sample and the statement sample. For alphabet A, it represents the application of the methodology, while for B, it signifies the case where the methodology was not applied. For Total Duration, in this case, the duration converged to 33 days under all circumstances. Regarding Total Cost, a lower amount was obtained when the methodology was applied in all iterations and tries. In Figure 6, a line graph connecting the average points of five tries for each iteration is presented. Upon examining the line graph, it is evident that the slope is smooth, and it becomes even smoother when transitioning from 50 to 150 iterations to 150 to 300 iterations. This indicates a closer approach to cost-duration optimization as the number of iterations increases. Furthermore, when the methodology is applied, the graph shows a smoother trend compared to when it is not applied, and there is a similarity in values between 150 and 300 iterations.

Through these results, it can be observed that when applying the Methodology, it continuously learns better points compared to when it is not applied, thereby preventing falling into local optima. Furthermore, it was confirmed that faster convergence towards the optimal point allows for reducing the number of iterations required for optimization, leading to time savings and thus improving optimization performance.

5. CONCLUSION

In this study, we proposed a methodology for preventing local optima and accelerating the attainment of optimal points in construction schedule simulation based on reinforcement learning. This was achieved by leveraging simulations incorporating equipment combinations and productivity data derived from DES, along with risk considerations. Through the application of reinforcement learning, we demonstrated the ability to mitigate local optima phenomena and expedite the convergence to optimal points, thereby reducing the optimal time in construction scheduling. In this study, this method was utilized to induce learning towards higher efficiency by leveraging the relationship between productivity and unit cost during the process of selecting the optimal equipment combination. However, even if other essential factors, such as those considering site conditions, in addition to equipment combinations and risk, are researched, or if a construction simulation is developed that optimizes by selecting factors other than the optimal equipment combination through reinforcement learning, this methodology can still be effectively utilized as long as it identifies elements that facilitate more efficient learning when these resources are selected. We anticipate that this methodology developed by our research team will not only be applied to the construction schedule simulation under development but also to various other construction schedule simulations. We hope that it will significantly contribute to the advancement of construction scheduling optimization technology.

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