A hybrid approach for solving multi-mode resource-constrained project scheduling problem in construction

Jerzy Hubert Rosłon* and Janusz Edward Kulejewski

Abstract: Practical problems in construction can be easily qualified as NP-hard (non-deterministic, polynomial-time hard) problems. The time needed for solving these problems grows exponentially with the increase of the problem’s size – this is why mathematical and heuristic methods do not enable finding solutions to complicated construction problems within an acceptable period of time. In the view of many authors, metaheuristic algorithms seem to be the most appropriate measures for scheduling and task sequencing. However even metaheuristic approach does not guarantee finding the optimal solution and algorithms tend to get stuck around local optima of objective functions. This is why authors considered improving the metaheuristic approach by the use of neural networks.

Introduction

The resource-constrained, project-scheduling problem (RCPSP) is commonly known in scientific literature [1, 2]. In its classic form, RCPSP aims to minimize the makespan or total duration of a project subject to precedence relations between the activities and the limited renewable resource availabilities. The problem is known to be NP-hard (non-deterministic, polynomial-time hard) [1].

The multi-mode, resource-constrained, project-scheduling problem (MRCPSP, sometimes also known as MMRCPSP) is a generalized version of RCPSP. The term multi-mode means that the schedule activities can be performed in different modes (ways). Each mode has a specific duration and specific resource requirements [2]. Due to such an approach, it is possible to take into account situations in which, for example, additional resources can be allocated to a task in order to shorten its duration. However, with the introduction of the additional decision variables, the amount of time required to solve the problem increases (it grows exponentially with the increase of the problem’s size). As a result, the computational time required for solving a MRCPS problem instance is longer than that of a similar RCPS problem instance without multiple modes. The problem can be even harder if one introduces probabilistic/fuzzy data [3, 4]. For this reason, it is of utmost importance to create efficient computational algorithms/approaches for solving MRCPS class problems.

Mathematical methods do not enable finding acceptable solutions to complicated, practical construction problems within an acceptable period of time. That is why, in the view of many authors, metaheuristic algorithms seem to be the most appropriate measures for scheduling and task sequencing [1, 4]. Among the approaches for solving MRCPS with the use of metaheuristics, several algorithms were proposed and tested by various authors: genetic algorithms (GA) [2, 5]; simulated annealing (SA) [6]; tabu search (TS) [7, 8]; particle swarm optimization (PSO) [9]; ant colony optimization (ACO) [10], or hybrid algorithms/approaches [11]. Recent research shows that tabu search is one of the most efficient metaheuristics for such combinatorial problems [4, 7, 8]. A summary of the methods used for solving MRCPS instances in construction can be found in [1].
Unfortunately, in particularly complicated cases, even metaheuristic approach does not guarantee finding the optimal solution and algorithms tend to get stuck around local optima of objective functions (especially while MR-CPS problems which are more complicated than corresponding RCPSP problems). That is why alternative approaches to solving scheduling problems are being constantly developed, some include hybrid or multi-stage algorithms, other artificial neural networks (ANN) (such approach was developed by the authors of the manuscript).

Colak et al. [12] proposed adaptive metaheuristic procedure based on neural networks: for the first iteration, the weights for all the activities are the same (the first iteration solution is identical to the single-pass heuristic solution). In the subsequent iterations, the weights are modified and weighted processing times recalculated and later the same heuristic is applied. Rondon et al. [13] analyzed the scheduling process on single machine supported by neural networks. The operating variables studied included e.g. processing time, setup time, deadline time, duetade time, priority. Adeli with other contributors [14, 15] used Neural Dynamics Model (developed by Adeli and Park) for different types of construction projects to minimize total project cost by creating functions for direct cost calculations on the base of resource assignment to the given task. Jaberi & Jaberi [16] proposed Potts mean field annealing neural network based heuristic. In all these works, neural networks components were used simultaneously with the metaheuristic algorithms. More information on neural networks for construction schedules optimization can be found in [17].

Unfortunately, the above mentioned methods have some shortcomings. For example, they are restricted to 1-5 modes (while in reality construction companies are facing much more possible options/modes). Also most of them are focused on makespan optimization, excluding crucial, financial aspects of construction projects. Even when tackling time cost trade-off, authors are only minimizing project total cost, omitting other practical aspects and indicators important for contractors like NPV or maximum monthly cash demand. Such indicators are crucial for the efficient management of a construction company [1, 4, 7, 8]. To make up for these shortcomings, new hybrid approach for solving multi-mode resource-constrained project scheduling was developed by the authors of this manuscript.

2 Methods

In the considered model MRCPSP can be formulated as follows: a project network $G (N, A)$ (in AON format) has $N$ set of activities numbered from 0 (the start dummy node) to $n+1$ (the end dummy node), $A$ is the set of activity pairs between which exists a finish-start precedence relationship (with a time lag $\geq 0$). A schedule $S$ is defined by a vector of activity start $s_i$ and its corresponding finish $f_i$ times. $T$ is a deadline given by the client.

In the literature authors generally focus on renewable resources (e.g. workers, machinery) [1, 12]. In presented model authors considered non-renewable resources (money). $R^v$ is a set of such resources, its availability can be stated as $a^v_i, l \in R^v$. This allows for a greater flexibility for the contractor, i.e. there are more modes for activities, each representing the possibility of change not only in employment, but also materials, technology, machinery or possibility of hiring subcontractors.

The decision variables were limited to the mode of activity omitting task sequencing. That is why the researched method is dedicated to the projects in which predecessor-successor relationships between activities are set. It focuses on economic aspects of scheduling. Each activity $i \in N$ can be performed in $m_i$ different execution modes, $m_i \in M_i = \{1, \ldots, |M_i|\}$. The duration of the activity $i$ performed in the mode $m_i$ is $d_{imi}$. Each mode $m_i$ requires $r^{v}_{imi}$ non-renewable resources. The schedule is feasible if all precedence and resource constraints are satisfied:

\begin{align}
  s_0 &= 0, \quad (1) \\
  s_i &\in \mathbb{Z}^+, \forall i \in N, \quad (2) \\
  f_i &= s_i + d_{imi} \leq s_j, \forall \{Pred(j)\}, \quad (3) \\
  \sum_{i=1}^{N} r^{v}_{imi} &\leq a^v_i, \forall l \in R^v, \forall m_i \in M_i, \quad (4) \\
  s_{n+1} &\leq T, \quad (5)
\end{align}

where:

1. the start dummy node time = 0, construction begins in assumed zero time,
2. all time data is integer and positive (for all activities except for start dummy node),
3. predecessors / successor rule for activities, no task can start before finishing of its predecessors,
4. the resource usage constraint,
5. the project cannot finish later than on deadline (agreed with the client).
An approach for construction project scheduling

The main optimization criterion was selected: reducing (minimizing) maximum monthly demand for cash (CDmax):

$$\text{Min} : CD_{\text{max}} = \max(\text{CD}_k),$$  \hspace{1cm} (6)

where:

$$\text{CD}_k = IF_k - OF_k,$$  \hspace{1cm} (7)

$k$ is a given month and $k \in K = \{1, \ldots, \lfloor s_{n+1}/21 \rfloor \}$ (21 workdays a month),

$CD_k$ is a demand for cash for a month $k$,

$IF_k$ is a contractor’s cash income for a month $k$,

$OF_k$ is a contractor’s cash outcome (including direct and indirect costs) for a month $k$.

This criterion is rather rarely used in the literature, nevertheless it is a very important factor for construction contractors as it limits their operational capability and is strictly connected to the cash flow [8].

In the cited literature neural networks components were used simultaneously with the metaheuristic algorithms. In the proposed approach, neural networks are used once, to limit variables range therefore allowing for simplification of the problem instance. The proposed approach (approach for MRCPSG transformation with the use of artificial neural networks – AMTANN) consists of the 5 following steps:

1. In the first step software calculates problem instance to obtain single-pass metaheuristic solution, at the same time saving interim results. These results are later used as a training sample for the neural network.
2. The second step includes neural network processing to establish the weights for each variable.
3. The next step includes studying of profiles in order to determine relationships between predictors (variables) and the response (output), and interactions between predictors. Several profiles are studied in order to find certain unfavorable combinations.
4. Basing on the findings from the previous step, some combinations are excluded resulting in the decrease in the range of the chosen variables values. The limited range means that some modes are excluded and the initial problem instance is transformed into instance that is easier to solve (has less possible variants).
5. In the final step software repeats single-pass metaheuristic calculation, this time optimizing simplified problem instance.

3 Numerical Example

In the presented example, contractor builds an object with a defined list of summary tasks (work packages) such as ground works, foundation works, shell, roofing, finishing works etc. The original network diagram is presented in Figure 1, schedule data is presented in Table 1.

Figure 1: Network diagram of the example construction project

Financing assumption: invoices are issued every month with payments after 14 days, discount rate is 10%, indirect costs 8 900 USD/day; penalty of each day of overrun 5 000 USD. Due-to-time – 23 months = 483 workdays (21 workdays a month). Initially assumed profit at the level of 14%.

Initial version of the schedule included 15 variables: $X_1$-$X_{15}$ (parameters), each representing selection of a mode for one of the 15 activities (activities 2-16). In this scenario there were up to 73 (activity 13) modes per activity. In total there were $2.3 \times 10^{11}$ combinations possible.

First, authors calculated initial solutions, to this end authors used tabu search algorithm – TS. It was developed by Fred Glover in 1980s [18]. The basic idea behind this algorithm is to search the solution space by a sequence of moves. In this sequence, some moves are considered tabu moves – they are forbidden. The TS algorithm avoids getting stuck in local optima by storing the information about previously checked solutions in form of tabu lists. The list is growing as the algorithm proceeds. However, when it reaches its maximum capacity, the oldest entries of tabu list are being overwritten be the new ones [18].

Interim results of single-pass metaheuristic TS solutions were saved for neural network processing. In this stage weights were established for each variable. Authors analyzed multiple networks to find the best suitable parameters.

Final calculations were done with a feedforward neural network for 15 inputs (representing each variable), 1 hidden layer (with 4 neurons), and 1 output (Figure 2). Several options were tried in terms of training and validation.
Figure 2: The best performing topological structure (architecture) of the Multilayer Perceptron used in numerical example.

Profiles obtained by the use of ANNs were studied. At this stage 6 predictors’ intervals were decreased. Studies showed that no matter which combinations were set for other variables, the outcome (CDmax) was getting better with the increase (or decrease) of a given parameter. As a result, the ranges of the said 6 parameters were cut in half leaving higher values (or lower values in case of decrease).

The change of the variables range allowed for simplification of the example to 6.5 × 10^9 possible results. The new, limited data for scheduling is presented in Table 2. Finally, the simplified problem instance was calculated by the TS metaheuristic algorithm.

### 4 Results

To test the efficiency of artificial neural networks in terms of problem instance simplification authors carried out tests. Metaheuristic algorithm was used for calculations using different settings to compare results achieved for the initial and simplified problem instance. 30 different settings were tested. Results of CDmax optimization are presented in Table 3.

In 26 cases AMTANN provided results better than classic single-pass metaheuristic calculation – TS (87% success rate: that is the percentage of success among a number of attempts), in one case the results were equal (test no. 16), in 3 cases slightly worse (tests 6, 8, 11). The mean of the improved results was almost 3 times greater (absolute value) than the mean of worsened results. Although the absolute improvement of the results is not large, it proves that AMTANN can be used for MRCPSp simplification.

| Id. | Description                  | Minimum duration [days] | Maximum duration [days] | Maximum cost [USD] | Minimum cost [USD] |
|-----|------------------------------|-------------------------|-------------------------|-------------------|-------------------|
| 1   | Start                        | -                       | -                       | -                 | -                 |
| 2   | Excavation                   | 6                       | 10                      | 514800            | 269096            |
| 3   | Foundations                  | 3                       | 6                       | 848353            | 406276            |
| 4   | Cellars                      | 3                       | 4                       | 256740            | 117468            |
| 5   | Structure                    | 11                      | 18                      | 593632            | 120298            |
| 6   | Roof structure               | 3                       | 5                       | 199000            | 185001            |
| 7   | Roof covering                | 2                       | 3                       | 366950            | 336950            |
| 8   | External Installations       | 220                     | 250                     | 423500            | 353500            |
| 9   | Foundation covering          | 6                       | 9                       | 661513            | 369966            |
| 10  | Partition walls              | 10                      | 14                      | 888850            | 588885            |
| 11  | Internal plasters            | 10                      | 17                      | 531383            | 135383            |
| 12  | Facade                       | 22                      | 24                      | 564386            | 554881            |
| 13  | Electrical installations     | 183                     | 255                     | 59946             | 29289             |
| 14  | Sanitary installations       | 3                       | 5                       | 38567             | 26233             |
| 15  | Painting                     | 70                      | 81                      | 229100            | 200291            |
| 16  | Terrain architecture         | 4                       | 6                       | 73450             | 66592             |
| 17  | Finish                       | -                       | -                       | -                 | -                 |
Table 2: The example project schedule data – limited range

| Id. | Description             | Minimum duration [days] | Maximum duration [days] | Maximum cost [USD] | Minimum cost [USD] |
|-----|-------------------------|-------------------------|-------------------------|--------------------|--------------------|
| 1   | Start                   | -                       | -                       | -                  | -                  |
| 2   | Excavation              | 8                       | 10                      | 391948             | 269096             |
| 3   | Foundations             | 4                       | 6                       | 700994             | 406276             |
| 4   | Cellars                 | 4                       | 4                       | 117468             | 117468             |
| 5   | Structure               | 15                      | 18                      | 323156             | 120298             |
| 6   | Roof structure          | 3                       | 5                       | 199000             | 185001             |
| 7   | Roof covering           | 3                       | 3                       | 336950             | 336950             |
| 8   | External Installations  | 235                     | 250                     | 388500             | 353500             |
| 9   | Foundation covering     | 6                       | 9                       | 661513             | 369966             |
| 10  | Partition walls         | 10                      | 14                      | 888850             | 588885             |
| 11  | Internal plasters       | 10                      | 17                      | 531383             | 135383             |
| 12  | Facade                  | 22                      | 24                      | 564386             | 554881             |
| 13  | Electrical installations| 183                     | 255                     | 59946              | 29289              |
| 14  | Sanitary installations  | 3                       | 5                       | 38567              | 26233              |
| 15  | Painting                | 70                      | 81                      | 229100             | 200291             |
| 16  | Terrain architecture    | 4                       | 6                       | 73450              | 66592              |
| 17  | Finish                  | -                       | -                       | -                  | -                  |

Figure 3: The cash flow for respective periods - the best result [USD]

The cash flow for respective periods and project schedule for the best calculated case are presented in Figure 3 and 4.

5 Discussion

The results are promising for construction practitioners. Although AMTANN did not achieve 100% success rate (87% success rate was obtained) in the preliminary tests, its first step include single-pass metaheuristic calculation. So even if the proposed approach cannot find better solution in the final step, the user already has the best solution (can be sub-optimal) stored (result of the first step). It means that the user does not risk worsening of the classic metaheuristic solution, at the same time having a great chance for its improvement.
Table 3: Results comparison.

| Test no. | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      | 10     |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| TS       | 1008622 | 1008470 | 1010047 | 1010965 | 1009578 | 1010662 | 1010965 | 1007383 | 1010965 | 1010965 |
| AMTANN   | 1007533 | 1006694 | 1008002 | 1008002 | 1007852 | 1010965 | 1008173 | 1008497 | 1009559 | 1009559 |
| Difference | -1089,000 | 1776,411 | 2045,021 | 2962,908 | 1726,432 | -302,213 | 2791,571 | -1113,37 | 1405,264 | 1405,264 |

| Test no. | 11     | 12     | 13     | 14     | 15     | 16     | 17     | 18     | 19     | 20     |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| TS       | 1006749 | 1006749 | 1006749 | 1008622 | 1006749 | 1006749 | 1005647 | 1006749 | 1007065 | 1008154 |
| AMTANN   | 1007065 | 1004992 | 1004992 | 1007533 | 1006170 | 1006749 | 1004992 | 1005647 | 1006749 | 1006749 |
| Difference | -316,040 | 1756,579 | 1756,579 | 1089,223 | 578,638 | 0      | 654,412 | 1102,167 | 316,04  | 1405,264 | 1405,264 |

| Test no. | 21     | 22     | 23     | 24     | 25     | 26     | 27     | 28     | 29     | 30     |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| TS       | 1008622 | 1010047 | 1010965 | 1006749 | 1006749 | 1010047 | 1010965 | 1010965 | 1010965 | 1007383 |
| AMTANN   | 1007533 | 1008002 | 1008002 | 1004992 | 1004992 | 1008002 | 1008002 | 1008002 | 1008002 | 1004992 |
| Difference | 1089,223 | 2045,021 | 2962,908 | 1756,579 | 1756,579 | 2045,021 | 2962,908 | 2962,908 | 2962,908 | 1756,579 |

**Summary**

|     | Minimum | Maximum | Mean   |
|-----|---------|---------|--------|
| TS  | 1005647 | 1010965 | 1008683 |
| AMTANN | 1004992 | 1010965 | 1007233 |

**Difference**

|     | 654,412 | 0  | 1450,397 |

all values for rows TS, AMTANN and difference are given in USD

Figure 4: The project schedule - the best result

AMTANN proves that metaheuristic algorithms can be supported by artificial neural networks (in terms of problem instances simplification) in order to improve schedule optimization results for MRCPS in construction. In the future authors plan to research further the described topic. In particular: test more instances, additional variables reduction options and other machine learning approaches. Should the future tests be also successful, authors will consider developing automatic tool (software). Such tool would significantly reduce the time needed for AMTANN performance, increasing its value for the construction industry.

At the same time authors would like to underline that metaheuristic approach does never guarantee finding the optimal solution, however it seems perfect for solving complicated, NP-hard class problems because it allows for computing sub-optimal, acceptable solutions within an acceptable time frame.

**Acknowledgement:** Authors would like to thank Faculty of Civil Engineering, Warsaw University of Technology for providing software and hardware necessary for the research.

**References**

[1] Roslon J., The multi-mode, resource-constrained project scheduling problem in construction: state of art review and research challenges, Technical Transactions, 2017, DOI: 10.4467/2353737XCT.17.070.6427
Van Peteghem V., Vanhoucke M., A genetic algorithm for the preemptive and non-preemptive multi-mode resource-constrained project scheduling problem. European Journal of Operational Research, 2010, 201(2), 409-418

Ibadov N., Fuzzy estimation of activities duration in construction projects, Archives of Civil Engineering, 2015, 61, 23–34, DOI: 10.1515/ace-2015-0012

Roslon J., Zawistowski J., Construction projects’ indicators improvement using selected metaheuristic algorithms, Procedia Engineering, 2016, 153, 595-598, https://doi.org/10.1016/j.proeng.2016.08.198

Magalhães-Mendes J., A two-level genetic algorithm for the multi-mode resource-constrained project scheduling problem, International Journal of Systems Applications, Engineering & Development, 2011, Issue 3, Volume 5

Józefowska J., Mika M., Różycki R., Waligóra G., Węglarz J., Simulated annealing for multi-mode resource-constrained project scheduling, Annals of Operations Research, 2001, 102(1-4), 137-155

Kulejewski J., Zawistowski J., Metoda symulacyjna wyznaczania wielkości buforów stabilizujących harmonogramy budowlane, Budownictwo i Inżynieria Środowiska 2: 2011, 563-572

Roslon J., Porównanie algorytmów genetycznego i przeszukiwania tabu wykorzystanych do szeregowania zadań w budownictwie. Materiały Budowlane, 2016, DOI: 10.15199/33.2016.06.18

Zhang H., Tam C. M., Li H., Multimode project scheduling based on particle swarm optimization, Computer-Aided Civil and Infrastructure Engineering, 2006, 21(2), 93-103

Urbaniaik M., Zastosowanie algorytmu mrówkowego do op- tymalizacji czasowo-kosztowej projektów informatycznych, Ekonometria, 2012 (38), 343-355

Ranjbar M., De Reycl B., Kianfar F., A hybrid scatter search for the discrete time/resource trade-off problem in project scheduling, European Journal of Operational Research, 2009, 193(1), 35-48

Colak S., Agarwal A., Erenguc S., Multi-mode resource-constrained project-scheduling problem with renewable resources: new solution approaches. Journal of Business & Economics Research (Online), 2013, 11(1), 455

Rondon R. L. A., da Carvalho A. S., Hernandez G. I., Neural network modelling and simulation of the scheduling, In Innovation in Manufacturing Networks, 2008, 231-238, Springer, Boston, MA

Adeli H., Karim A., Scheduling/cost optimization and neural dynamics model for construction, Journal of Construction Engineering and Management, 1997, 123(4), 450-458

Senouci A. B., Adeli H., Resource scheduling using neural dynamics model of Adeli and Park. Journal of Construction Engineering and Management, 2001, 127(1), 28-34

Jaberi M., Jaberi M., A multi-objective resource-constrained project-scheduling problem using mean field annealing neural networks, J Math Comput Sci, 2014, 9, 228-239

Adeli, H., Karim A., Construction scheduling, cost optimization and management, 2014, CRC Press.

Fridgeirsson T.V., Roslon J., Optimisation of construction processes, 2017 Civil Engineering Faculty of Warsaw University.