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Optimizing lift operations and vessel transport schedules for disassembly of multiple offshore platforms using BIM and GIS

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ABSTRACT

As the coming decades will witness a big trend in the decommissioning of offshore platforms, simultaneously disassembling topsides of multiple offshore platforms is getting increasingly common. Considering high risk and cost of offshore operations, module lift planning among multiple offshore platforms with transport vessels is required to be carefully conducted. The lift planning usually contains two main parts: module layout on vessels planning and vessel transport schedules arrangement. In contrast to the current experience-driven module lift planning, this paper formulates the lift planning optimization problem and develops a web system integrating building information modeling (BIM) and geographical information system (GIS) to efficiently disassemble topsides for multiple offshore platforms. BIM provides detailed information required for planning module layout on vessels and GIS contains the management and analysis of geospatial information for the vessel transport schedule arrangement. As for module layout optimization, three heuristic algorithms, namely genetic algorithm (GA), particle swarm optimization (PSO), and firefly algorithm (FA) are implemented and compared to obtain the module layout with the minimum total lift time. While for vessel transport schedule, graph search technique is integrated with a developed schedule clash detection function to obtain the transport schedule with the minimum sailing time. The proposed optimization algorithms and techniques are integrated into a developed BIM/GIS-based web system. An example of three offshore platforms with eighteen modules in total is used to illustrate the developed system. Results show that the developed system can significantly improve the efficiency of lift planning in multiple topsides disassembly. The developed BIM/GIS-based web system is also effective and practical in the resource allocation and task assignment among multiple locations, such as construction sites, buildings, and even cities.

1. Introduction

Offshore platforms are large structures with functional modules to drill and process oil and natural gas from the seabed. An offshore platform generally has a lifetime of 30 to 40 years. The decommissioning of offshore platforms is the most important concern of the stakeholders when platforms are reaching their end of service lives. The big markets of offshore platform decommissioning for the coming decades around the world, such as the North Sea [1], coastal of Southern California [2], and Asian Pacific areas [3], were presented in [4]. There are different types of offshore platforms, while fixed platforms are one of the commonly used offshore platform types in the world. Topsides disassembly is an important task during the decommissioning of fixed platforms considering the cost, time, and risk. The main work of topsides disassembly is to lift the functional modules from the deck of platforms to transport vessel. Since functional modules are usually big and heavy, the module layout on a vessel can impact the total module lift time and stability of the transport vessel. Especially, the unstable offshore environment is a critical concern during the disassembling phase [5]. Therefore, planning and optimizing module layout on transport vessels is necessary.

The study of functional module layout on transport vessel is still limited. Although Tan et al. [6] studied the module layout problem, the study only optimized module layout in a “one platform one vessel” scenario. However, a stakeholder usually owns several offshore platforms, which are located in clusters. It is meaningful and necessary to share vessel resources among multiple offshore platforms. Therefore, decommissioning multiple offshore platforms is getting common. In the North Sea, increasing number of stakeholders tend to decommission multiple offshore platforms simultaneously to share decommissioning

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knowledge and take full advantages of available equipment, such as huge heavy lift vessel. For example, ConocoPhillips (U.K.) Limited plans to decommission three offshore platforms in Lincolnshire Offshore Gathering System [7]. Centrica North Sea Limited has started to decommission four offshore platforms [8,9] in Audrey filed simultaneously. Considering the size and weight of the functional modules, multiple transport vessels are required and shared by the platforms. The module assignment, meaning which module should be assigned to which predetermined locations on which transport vessel, is similar to quadratic assignment problem (QAP). Since there is no known algorithm for solving QAP in polynomial time, and even some cases require long computational time, this problem is usually treated as non-deterministic polynomial-time hardness problem (NP-hard problem). QAP has already been studied in the manufacturing industry and the building construction industry for decades. Heuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), and the recently developed firefly algorithm (FA) have been commonly applied to solve QAP with promising performance and advantages over computational time. However, the study of formulating module lift problem as QAP to optimize the module layout on transport vessel with different heuristic algorithms is still limited.

In addition to the module lift operations, module transport is another important part of the topsides disassembly of multiple offshore platforms. After obtaining optimal module layout on all transport vessels, the platforms to be visited for each vessel are determined. Since offshore platforms are usually far away from each other and the weight of loaded modules has an impact on the sailing speed of transport vessels, the transport schedule of each vessel to offshore platforms requires being carefully planned considering the potential unexpected environment such as hurricanes and storms. The optimization problem of vessel transport schedule can be treated as a graph search problem especially when the number of offshore platforms to be decommissioned increases. However, unlike traditional graph search problem [10,11], where each edge usually contains no more than two weights that represent the travel cost or distance between two nodes, the number of weights (sailing time between two platforms) on each edge varies according to the number of platforms to be visited by each vessel. Although the study of developing efficient search algorithms on graph has been conducted for decades [12] and applied to various fields [13] such as supply chain management and path planning, graph search is still lacking in the vessel transport schedule problem studied in this paper.

To optimize lift operations, including module layout on vessels and vessel transport schedule for topsides disassembly of multiple offshore platforms, information such as module locations on different offshore platforms, module weight, predetermined locations on each vessel, size of all offshore platforms and vessels, distances among platforms, and distances between each platform and onshore factory site is required. Building information modeling (BIM) has been increasingly used to provide detailed geometric and semantic information for elements in civil engineering projects for the past decade. Geographic information system (GIS) has advantages over geospatial data management and spatial analysis for the objects with multiple spatial scales, from nationwide and citywide issues to a construction site or a building. Increasing number of researchers try to take advantage of the benefits of BIM and GIS by integrating them. Therefore, this study integrated BIM and GIS on web technology to provide enough information for the optimization objectives. Heuristic algorithms will be implemented to optimize the lift operations, and graph search technique will be applied to plan the vessel transport schedule.

The rest of this paper is outlined as follows. Section 2 reviews related work on lift planning optimization that has been previously conducted. A BIM/GIS-based web system for optimizing module lift operations and vessel transport schedule is proposed in Section 3. To illustrate the proposed system, an example is used in Section 4. Section 5 discusses the study and concludes the study with limitations and future work.

2. Related work

2.1. Facility layout problem: quadratic assignment problem

Determining facility placement in production systems, plant areas, construction sites, and other spaces is defined as the facility layout problem (FLP) [14–16]. Minimizing the materials handling cost based on distances and material flows among facilities is the most common objective used when formulating the mathematical models. FLP can be categorized into different models according to the way of layout problem formulation. Quadratic assignment problem (QAP) model, mixed integer programming (MIP) problem model, and graph theory model are three of the most commonly studied models for FLP [14,15]. QAP is considered as a challenging combinatorial optimization problem [17], which assigns facilities to locations in a way that each facility is assigned to one location [18]. One process to be studied in this paper is lifting modules from the offshore platform to the predetermined locations on heavy lift vessel. Therefore, the module lifting process can be formulated as QAP without considering material flow between any two modules on the vessel.

QAP, as a classical NP-hard combinational optimization problem, has been studied since 1957 by many researchers using developed exact and heuristic approaches [19]. Among the heuristic approaches, genetic algorithm (GA) and particle swarm optimization (PSO) were commonly used to solve QAP models. For the GA-based QAP studies, Tate and Smith [20] implemented GA to solve QAP problem and it performed well compared with the previously studied heuristic algorithms. Li and Love [21] used GA to plan facilities on construction sites and the efficiency of GA in solving the construction site-level facility layout was demonstrated. Other GA-based QAP studies not only used GA to solve the assignment problem, but also tried to improve GA performance by incorporating greedy principles [22], developing effective operators [23], and designing a parallel GA with multiple processors in a GPU [24].

As for PSO-based QAP studies, Lv et al. [25] used PSO to solve quadratic assignment problem and proposed a new particle representation for the problem. Gong and Tuson [26] generalized PSO operator in a formal manner using forma analysis and the obtained results are comparable to a GA. In addition, PSO was also integrated with other methods to well solve quadratic assignment problem. For example, Liu et al. [27] designed a fuzzy scheme to extend traditional position and velocity of the particles to fuzzy matrices. Zhao et al. [28] introduced fuzzy PSO to handle multi-objective QAP.

In addition to GA and PSO, another heuristic algorithm named firefly algorithm (FA) [29,30], which was first proposed in late 2007 and 2008 [31,32] and was based on the flashing patterns and behavior of fireflies, can also be used for QAP. For example, Durkota [33] proposed a way to adjust FA to solve discrete problems such as QAP with permutation solutions. Fister Jr. et al. [34] applied FA, hybridized with local search heuristic, to optimize the combinational problem called graph 3-coloring problem. The results of using FA were promising and showed that FA can also be applied to other combinational optimization problems.

Previous efforts of applying heuristic approaches to solving quadratic assignment problem are based on total handling cost or time among all the assigned facilities. However, in this study, no material flow exits among the lifted modules on the vessel. Total lift time of all modules is the objective function to be minimized, which means this study focuses on the process of heavy lifts between platforms and vessels. Although Tan et al. [6] studied lift planning and module layout arrangement for one platform and one heavy lift vessel, the study of QAP-based module lift among multiple offshore platforms and vessels is still lacking.

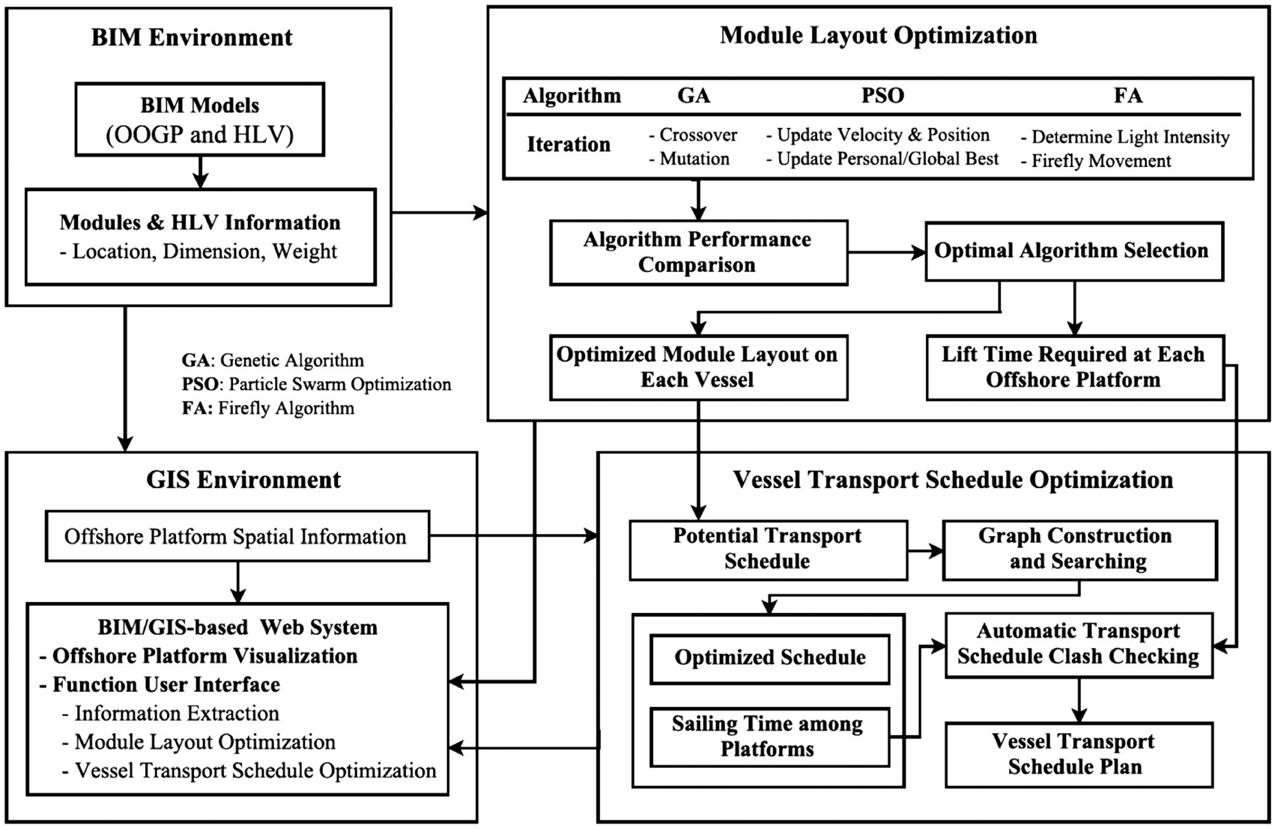

Fig. 1. The development framework of the proposed system.

2.2. Route optimization among multiple locations

Visiting multiple locations and conducting certain mission at each location is a common real-world manifestation. This issue is treated as traveling salesman problem (TSP) and Chinese postman problem (CPP), which have been studied for several decades. The TSP can simply be stated as if a traveling salesman wishes to visit exactly once each of a list of m cities and then return to the home city, what the least costly route is [35]. Complete historical development of TSP can be found in [36]. The CPP is to address the question of "how does one develop a tour or route that covers every street in the zone and brings the postman back to his point of origin having traveled the minimum possible distance" [37]. Many other similar problems such as street sweeping, snow plowing, garbage collection, meter reading and the inspection of pipes can be treated as CPPs. Both TSP and CPP are originally from the mathematical graph theory so that they can be addressed with the graph search algorithms.

In this study, similar to TSP and CPP, the vessel transport schedule arrangement problem is to determine the visiting sequence of each vessel to offshore platforms. However, there are still differences between TSP or CPP and the vessel transport schedule arrangement problem. In general, the graph theory problem consists of two parts: nodes and edges. Nodes are used to represent the locations to be visited, while edges are used to connect two nodes. Each edge is usually assigned with no more than two weights, which represent the cost required to travel between the two connected locations considering direction. In this study, edges represent the sailing time between two offshore platforms. Although the distance between two offshore platforms is fixed, the sailing speed varies with the total load of the vessel and the load depends on which offshore platforms have been visited by the vessel. Therefore, sailing time between two offshore platforms is impacted by vessel transport schedule and the possible sailing time will increase when platform number increases. According to the difference, the transport schedule problem of this study is more complicated; graph search technique will be implemented to try to optimize the problem.

2.3. BIM-GIS applications

BIM, as a 3D digital representation of geometric and semantic information of a facility, is increasingly applied in the architecture, engineering, and construction (AEC) industry [38]. However, the information provided by BIM is usually limited to a facility or a building level. GIS is a field that consists of geospatial database management, geospatial modeling, geospatial analysis and prediction, and geovisualization-based decision making [39]. Due to the strengths in the modeling at multiple spatial scales, GIS can be adaptive in the spatial and temporal analysis and decision making in various spatial objects, such as cities, infrastructure, buildings, and construction components [40,41]. Therefore, integrating BIM and GIS can take advantage of detailed facility or building information and geospatial information for more accurate and efficient decision making in the AEC fields.

BIM-GIS integration has been applied in addressing various practical issues. One of the most common fields of applying BIM-GIS integration is the facility management (FM) that the researchers integrated BIM and GIS for higher efficiency and better performance of management. Wang et al. [42] created a profiling approach to promote facility reuse. Kang and Hong [43] proposed a software architecture for effective BIM/GIS-based FM data integration. Liu and Issa [44] investigated the use of BIM and GIS information to obtain detailed information for facility operation and maintenance. In addition to building-level FM studies, BIM and GIS were also integrated for city-level FM studies, such as urban facility management [45] and utility information management [46]. Another popular field of BIM-GIS integration is the energy study. Wu et al. [47] proposed a virtual facility energy assessment planning tool by integrating BIM and GIS with a cloud infrastructure. Niu et al. [48] developed a BIM-GIS integrated

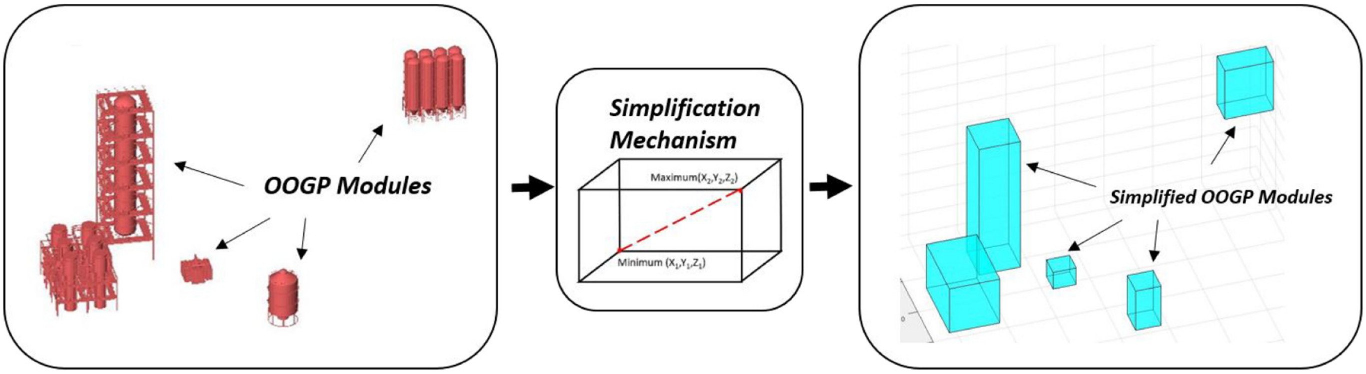

Fig. 2. Illustration of module geometry simplification [6].

web-based building energy data visualization system to facilitate collaboration between urban-level energy planning and building-level energy design. Yamamura et al. [49] proposed a BIM-GIS based urban energy planning system to encourage smart concept in Japan. In addition, BIM and GIS were also integrated and applied to many other fields, such as evacuation simulation under emergencies [50], 3D traffic noise mapping [51], crane layout planning on construction site [52], economic feasibility study [53] and earthwork operation [54] for highway, supply chain management [55], flood damage to a building [56], and risk control during construction [57].

Among the BIM/GIS-based applications, web-based platforms [48,58,59] usually take advantages over other platforms as no additional program installation was required. However, no studies have integrated BIM and GIS for offshore platform decommissioning including module lift operation and vessel transport schedule optimization, in which detailed facility information of modules and accurate spatial information of offshore platforms are required.

3. Development of proposed system

As shown in Fig. 1, the development framework of the proposed BIM/GIS-based web system for lift planning among multiple offshore platforms contains (1) BIM environment, (2) GIS environment, (3) module layout optimization, and (4) vessel transport schedule optimization. BIM environment (Part 1) contains detailed dimensions, locations, and semantic information of all functional modules and vessels. Information extraction and simplification are conducted in Part 1. GIS environment (Part 2) can not only provide required spatial information of all offshore platforms and onshore factory sites but also be integrated with BIM environment to develop the BIM/GIS-based module lift planning system for multiple offshore platforms. Module layout optimization (Part 3) and vessel transport schedule optimization (Part 4) are two core parts of the module lift planning system. Part 3 is based on the information obtained from Part 1. Heuristic algorithms namely genetic algorithm (GA), particle swarm optimization (PSO), and firefly algorithm (FA) are implemented to optimize module layout, and performance of the three implemented algorithms are compared to find the most efficient one. Based on the optimized results from Part 3 and spatial information obtained from Part 2, graph search technique integrated with a developed schedule clash detection function is used in Part 4 to optimize the vessel schedule of transporting all lifted modules to the onshore factory site. Part 3 and Part 4 are also integrated into Part 2, where an integrated BIM/GIS web-based system is developed to help plan module lift among multiple offshore platforms. More details of each part are discussed in the following sections.

3.1. System input

BIM, as one of the emerging information technologies applied in the AEC industry, is used to represent all functional modules on the offshore platform as well as the transport vessel in a 3D digital manner, where all required information is properly stored. Industry Foundation Classes (IFC), which is the main neutral file format for data exchange among BIM software, is used as the input file of the proposed BIM/GIS-based system to provide required information for module layout optimization part (see Section 3.2). To optimize module layout on vessels, module weight, module locations on offshore platforms, and predefined area locations on the vessel are required. The module weights are used to guarantee the stability of vessels. Before exporting IFC file from Revit, weight is added as property and assigned with the values according to historical manufacturing data. Then, the weights of modules can be automatically extracted from IFC file by accessing the entities of *IfcPropertySet* and *IfcPropertySingleValue*. As for geometric information of module, the geometry of modules is simplified, and location of the centroid of each module is automatically extracted as the locations for all modules on an offshore platform, using the approach that we have developed [6,60,61]. The module geometry simplification mechanism is illustrated as Fig. 2. The deck information of vessel can also be extracted following this same information simplification and extraction methodology, and then the centroid of each predefined area is used to represent its location.

In addition to obtaining required information from BIM environment for module layout optimization, to optimize transport schedules of vessels, spatial information of offshore platforms and onshore factory site are also required. GIS is a system that can capture, store, manipulate, and analyze all types of geo-spatial data. Therefore, GIS is used in the proposed system to provide all required spatial information to optimize transport schedule of vessels, which takes charge of moving all lifted modules from offshore platform to onshore factory site. IFC file that contains required information for module layout optimization is integrated into the GIS environment by data transformation among ArcGIS applications (see Section 3.4). The GIS environment integrated with IFC is then published as a web system. The proposed information extraction algorithm is realized in JavaScript and embedded into the published web system. By integrating BIM and GIS, the detailed information of functional modules to be lifted and spatial information of all offshore platforms and the onshore factory can be seamlessly combined within the developed BIM/GIS-based web system to provide required information for module lift planning. More details of the integration of BIM and GIS are introduced in Section 3.4.

3.2. Modules layout optimization

The purpose of module layout optimization is to obtain the optimal module layouts, which make the total lift time of all modules from offshore platforms to vessels the minimum and guarantee the stability of all vessels. As mentioned in Section 1, the module lift operation studied in this paper is similar to the QAP. However, compared to

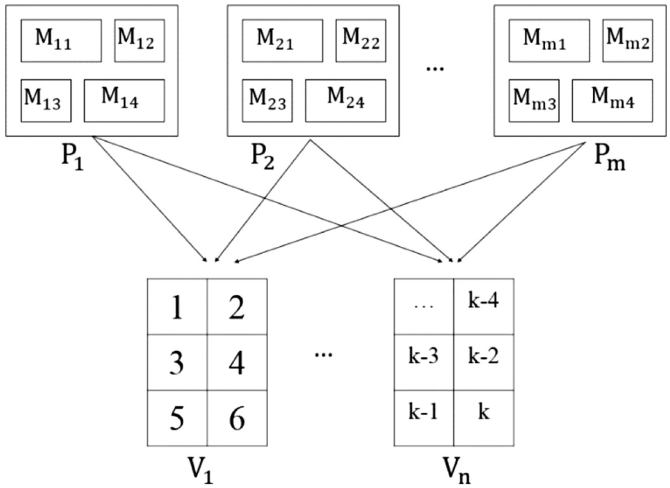

Fig. 3. Illustration of module being lifted from offshore platforms to vessels.

traditional QAP, the objective of this study is not to minimize the handling cost or material flows among facilities after being assigned but to minimize the total lift time during the module disassembly. Since offshore lift operations are more challenging than that on land, minimizing the total lift time of all disassembled modules can reduce the lift time, energy consumption, and potential safety hazards such as hoisting swing caused by unexpected sea waves and wind.

3.2.1. Module lift process

Before lifting functional modules, necessary preparation, including separating modules, removing chemical materials from modules, and fastening each module to avoid sliding off, should be conducted. After disassembly preparation, each module to be lifted is assigned a module ID as shown in Fig. 3. For each vessel, the deck is divided into several areas to load the disassembled modules, and all the predefined areas are also numbered from 1 to k. In addition, each defined area is assumed to be big enough to load any of the modules to be lifted. The total number of functional modules on the offshore platforms should be no more than k. The goal of the module lift process is to assign all indexed function module from m platforms to k predefined areas of n vessels. Different assignment plans (i.e. combination of module layout on vessels) result in different total lift time. As mentioned previously in this paper, the total lift time is used as the objective to be minimized. Therefore, the lift time of each module from an offshore platform to its arranged area on vessel is calculated and summarized to obtain the total lift time.

3.2.2. Single lift process decomposition

For each functional module, the lift operation contains three stages. First, the crane of the vessel lifts the module to a required height before rotation and radiation (see Fig. 4(a)). The required height should guarantee that the module does not clash with other structures on both the offshore platform and vessel. Then, the rotation and radiation are conducted simultaneously to move the module to be right above the planned area on the vessel (see Fig. 4(b)). Since offshore lift operations have a high level of risk, especially when conducting two lift operations simultaneously, the speeds of rotation and radiation should be well controlled to avoid unnecessary swing during lifting. The time required to finish the two lift operations may be different, the longer time is chosen as time consumed at this stage. Finally, the rotated and radiated module is lifted down to the planned area on the vessel as shown in Fig. 4(c). By calculating and summarizing the time consumed at each stage, the single lift time for each module layout can be obtained.

3.2.3. Objective function and solution representation

To evaluate each possible module layout on vessels, the total lift time of all modules from offshore platforms to vessels based on this module layout is used. The goal of optimizing module layout is to minimize the total lift time to avoid unnecessary safety issues that may be caused by being exposed to the offshore environment for a long time. The objective function is given as:

$$min\ f(t) = \sum_{i=0}^{n} \left(max\left(t_1^i, t_2^i\right) + t_3^i\right) \tag{1}$$

where $f(t)$ is the total lift time, n is number of modules to be lifted, i ($i = 0, \ldots, n$) is the ith module, $t_1{}^i$, $t_2{}^i$, and $t_3{}^i$ are the time required for rotation, radiation, and vertical lift for the ith module, respectively. Each time is calculated as follows:

$$t_1 = \arccos \alpha / v_1$$

$$t_2 = |l_1 - l_2| / v_2$$

$$t_3 = (h_{up} + h_{down}) / v_3$$

α: required angle to be rotated
l_1: distance between module and crane before the lift
l_2: distance between module and crane after lift
h_{up}: distance to be lifted up
h_{down}: distance to be lifted down
v_1, v_2, *and* v_3: rotation speed, radiation speed, and lift speed

Since each module is assigned with a predefined area on a certain vessel and all defined areas are already numbered, a permutation of 1 to $\boldsymbol{n}$ is used to represent each module layout (solution). For example, [8 4 7 1 5 3 2 6] is a layout with 8 modules. In this module layout, the 8th module will be lifted to the 1st predefined area on one of the vessels and the 5th will be lifted to the 5th predefined area. In addition, another safety concern is the stability of vessels. Therefore, for each layout (solution), the moment difference between the stern and bow (M_1) and

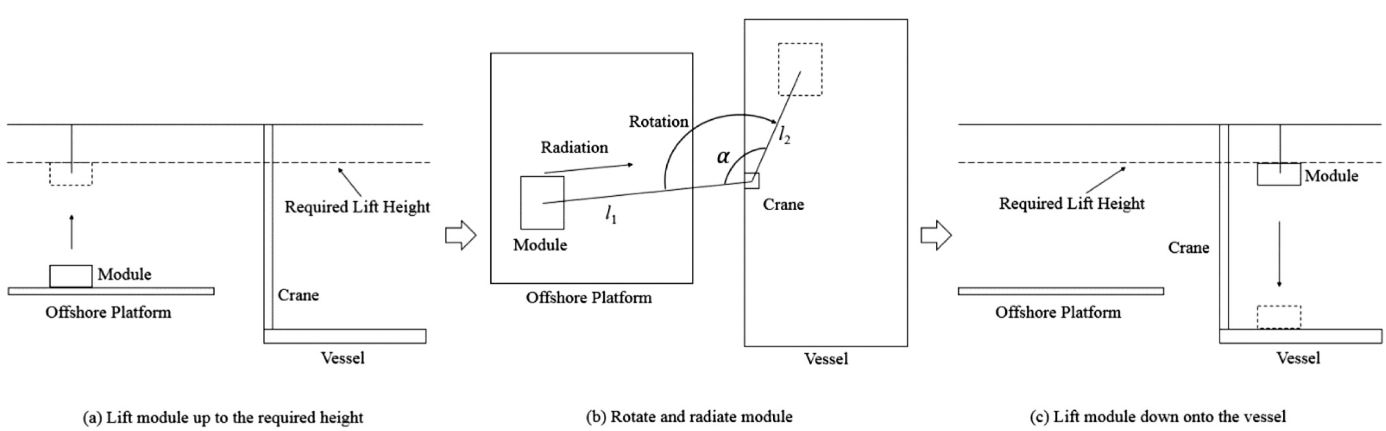

Fig. 4. Single lift process decomposition.

that between the left and right sides of each vessel (M_2) should be no more than a given tolerance. M_1 and M_2 caused by all modules can be calculated based on the information extracted from the BIM environment. Finally, based on the extracted module and vessel information, formulated objective function, and solution constraint, the module layout can be optimized with heuristic algorithms. The implementation of the three chosen algorithms is discussed in detail in the next section.

3.2.4. Optimization algorithms

The layout optimization problem studied in this paper is similar to QAP, which is also considered to be 'NP-hard'. Many heuristic algorithms, such as genetic algorithm (GA), particle swarm optimization (PSO), and firefly algorithm (FA), can be used to optimize the QAP-based layout problem. As mentioned in Section 2.1, this study considers QAP in a different perspective compared to traditional QAP. The objective to be optimized is to minimize total lift time when assigning all modules from offshore platforms to vessels rather than minimizing the material and handle flow among facilities after being assigned. GA, PSO, and FA are implemented respectively in this study to optimize module layouts on vessels and then the performance of these three algorithms are compared to select the optimal one for the module layout optimization in this study.

GA, which is inspired by evolution, is a common method of solving layout optimization problems due to its ease of implementation. GA usually tries to combine elements (crossover) from two potential solutions (parents) or to conduct mutation on one solution to produce a new solution (offspring) that is then evaluated by a fitness (objective) function. After evaluating the newly generated offspring, it is then compared with solutions in the initial population. If the new one is better, it is kept; otherwise, it is discarded. The iteration continues until the maximum generations are reached. Schematically, the GA can be summarized as the pseudo code as shown in Fig. 5.

PSO was initially introduced as a function optimization methodology inspired by the behaviors of fish schooling and bird flocking. PSO also solves a problem by initializing a population with a certain number of candidate solutions called particles. The particles move around in the search-space based on objective function over their positions and velocities. The movement of every particle is influenced by its local best-known position and also guided the global best-known position in the whole search space. More details of PSO can be seen from the pseudo code as shown in Fig. 6.

The last algorithm to be introduced is firefly algorithm (FA) that is based on the flashing patterns and behaviors of fireflies. FA is one of the latest artificial intelligence algorithms developed. The defined fireflies are unisex so that each firefly can be attracted to others by their attractiveness, which is proportional to the brightness. Both attractiveness and brightness decrease when the distance increases. For two fireflies, the less bright one will move towards the brighter one and their brightnesses are determined by the landscape of the objective function. FA is said to be superior when it comes to problems with many local optima and to return results extremely fast. Therefore, FA will also be implemented to optimize the module layout on vessels. The pseudo code of FA is shown in Fig. 7.

```
Objective function f(x)
Initialize a population (pop)
Evaluate pop and obtain the worst solution (S_w)
while (t < Max-Generation)
   Select two parents (P_1, P_2)
   Apply crossover and obtain new offspring (S_1, S_2)
   Evaluate S_1, S_2
   Select one parent (P_m)
   Apply mutation and obtain new offspring (S_m)
   Evaluate pop and obtain current S_w'
   if S_w' better than S_w
      S_w ← S_w'
   end if
end while
Obtain the best solution as the final solution: S_f
```

Fig. 5. Pseudo code of genetic algorithm (GA).

After implementing GA, PSO, and FA, convergences of the three algorithms are compared. Since all the three algorithms sharing the characteristics of starting iteration from an initialized population with a certain number of potential solutions, the population sizes (e.g. 30, 50, and 80) that are commonly used for population-based algorithms will be applied to explore that how population size impact the convergence of fitness of the three algorithms. Not only three algorithms with the same population size are compared, but also each algorithm with different population sizes are compared with each other. According to performance of GA, PSO, and FA, the most efficient and accurate algorithm is selected. Then, with the selected optimal algorithm, the optimized module layout on vessels can be obtained. With the optimized module layout, offshore platforms that each vessel should visit are determined. Since the transport schedule of vessels has an impact on the total offshore sailing time that is another safety concern, the optimization of vessel transport schedule is necessary. More details of the transport schedule optimization are discussed in the next section.

3.3. Vessel transport schedule optimization

According to the optimized module layout on each vessel, the offshore platforms that each vessel should visit can be determined. Since the weight of modules on offshore platforms varies and load of vessel impacts sailing velocity, the transport schedule of each vessel among offshore platforms has impact on the total offshore sailing time. As sailing on the sea faces many uncertainties such as huge waves and hurricanes that may cause safety issues to both vessel and humans, timely transporting all modules from multiple offshore platforms to land is necessary. Therefore, transport schedule among multiple offshore platforms for each vessel is optimized to reduce the total module transport time.

3.3.1. Potential transport schedule to graph

When module layout on each vessel is determined, the number (N) of offshore platforms that a heavy lift vessel needs to visit is obtained. The number of potential transport schedules for each vessel should be factorial of N. All potential transport schedules can be represented as a tree format (see Fig. 8). S and F represent the same location, the onshore factory site where vessels set off to lift and transport modules and return back to unload disassembled functional modules, and P_N is the n^{th} offshore platform to be visited. The weight on the line is the required sailing time between two locations. Transport time depends on the sailing velocity and sailing distance. Sailing distances among offshore platforms and on-land factory are fixed and sailing velocity usually varies according to weight of loaded modules.

The potential schedule can be converted to a graph to efficiently obtain the optimal schedule. All locations including S, F, and P_n are represented as nodes, which are connected by edges with weights on them. All nodes are then indexed. The weight, W_{ij}, are the vessel sailing time from i^{th} node to j^{th} node. W_{ij} is calculated according to carried load when vessel leaves i^{th} node. The whole constructed graph has $(N + 2)$ layers including S and F. From node S, the number of child nodes locate in the next layer decreases from N to 1. The number of total nodes increases when N gets bigger and the computational time to manually obtain the transport schedule with the least sailing time also increases. Therefore, graph search technique is necessary to be applied to automatically and efficiently obtain the transport schedule from the constructed graph.

```
Objective function f(x)
for each particle i = 1, ..., S
  Initialize the particle's position with a uniformly distributed random vector: x_i ~ U(b_lo, b_up)
  Initialize the particle's best known position to its initial position: p_i ← x_i
  if f(p_i) < f(g)
    Update the swarm's best known position: g ← p_i
  end if
  Initialize the particle's velocity: v_i ~ U(−|b_up − b_lo|, |b_up − b_lo|)
end for i
while (t < Max-Generation):
  for each particle i = 1, ..., S
    for each dimension d = 1, ..., n
      Pick random numbers: r_p, r_g ~ U(0,1)
      Update the particle's velocity: v_{i,d} ← ω v_{i,d} + Ø_p r_p (p_{i,d} − x_{i,d}) + Ø_g r_g (g_d − x_{i,d})
    end for d
    Update the particle's position: x_i ← x_i + v_i
    if f(x_i) < f(p_i)
      Update the particle's best known position: p_i ← x_i
      if f(p_i) < f(g)
        Update the swarm's best known position: g ← p_i
      end if
    end if
  end for i
end while
```

Fig. 6. Pseudo code of particle swarm algorithm (PSO).

```
Objective function f(x), x = (x_1, ..., x_d)^T
Initialize a population of fireflies x_i (i = 1, 2, ..., n)
Define light absorption coefficient γ
while (t < Max-Generation)
for i = 1: n all n fireflies
    for j = 1: i all n fireflies
      Light intensity I_i at x_i is determined by f(x_i)
      if (I_j > I_i)
      Move firefly i towards j in all d dimensions
      end if
    Attractiveness varies with distance r via exp[−γr]
    Evaluate new solutions and update light intensity
  end for j
end for i
Rank the fireflies and find the current best
end while
Post-process results and visualization
```

Fig. 7. Pseudo code of firefly algorithm (FA).

3.3.2. Graph search and schedule clash detection

After converting the potential schedules to a graph, some graph search technique can be used to obtain the schedule (location permutation) with the minimum cost (sailing time). The details of graph search technique used in this study are shown in Fig. 9. The search technique is initialized by creating an open list L and S is added to L. Each node has a cost value that represents the total sailing time required by the vessel to reach the node following the transport schedule. The node with minimum cost is then selected as the current node (*cn*) to extend L by adding the child nodes of *cn* to L. For every extension, *cn* is checked to see if *cn* is F or not. The extension continues until *cn* reaches F. When reaching F, the expected potential vessel transport schedule with the minimum cost is obtained.

Since heavy lifts at each offshore platform are dangerous offshore operations, one offshore platform only allows one vessel to conduct heavy lifts at a time. Although the vessel transport schedule with least sailing is obtained, potential schedule clashes may exist. Therefore, detecting schedule clashes is necessary. To detect schedule clash of a vessel, both sailing time between any two offshore platforms and lift time consumed at each platform for the vessel are required. Sailing time can be easily obtained during vessel transport schedule optimization and lift time can be obtained from the module layout optimization part (Section 3.2). With both sailing time and lift time, the detailed timeline of the selected vessel arrives and leaves each platform is obtained. Then, the arrival time and leaving time of one platform of the vessel are used to compare with that of the same platform of other vessels. If both arrival and leaving time is less than the arrival or more than leaving time of other vessels, the optimized transport schedule is used as the final vessel transport schedule plan; if not, necessary adjustment of the sailing time will be conducted to avoid the time clash. The graph search technique and schedule clash detection method are finally integrated into the developed BIM/GIS-based web system (see Section 3.3) to obtain the optimal transport schedule of each vessel.

3.4. Web-based BIM-GIS system development

To better take advantage of the proposed optimization methodologies for module lift process and module transport, a BIM/GIS-based web system was developed in this study. BIM provides the detailed information of all modules on different offshore platforms, while GIS provides spatial information for module transport schedule optimization. Since the commonly used neutral file formats for data exchange among BIM applications and GIS applications are Industry Foundation Classes (IFC) and shapefile respectively, developing a BIM/GIS-based web system requires integrating IFC and shapefile. The developed integration workflow of BIM and GIS is shown in Fig. 10. The whole integration process tries to open IFC file from BIM in ArcGIS platforms, a GIS environment. The original offshore platform models were first created in Revit, then exported as IFC files, and finally imported into ArcMap by using the Data Interoperability extension for ArcGIS, in which the IFC file was converted to multipatch (3D shape type of shapefile) stored in Geodatabase file (.dbf). Since GIS uses a world coordinate system, the offshore platforms in their local Cartesian coordinate system have to be geo-referenced to be correctly displayed, in which the location of those offshore platforms has to be adjusted, as well as their Z-values (height). The adjusted models in shapefile were then imported into ArcGIS Pro to be placed at the right position.

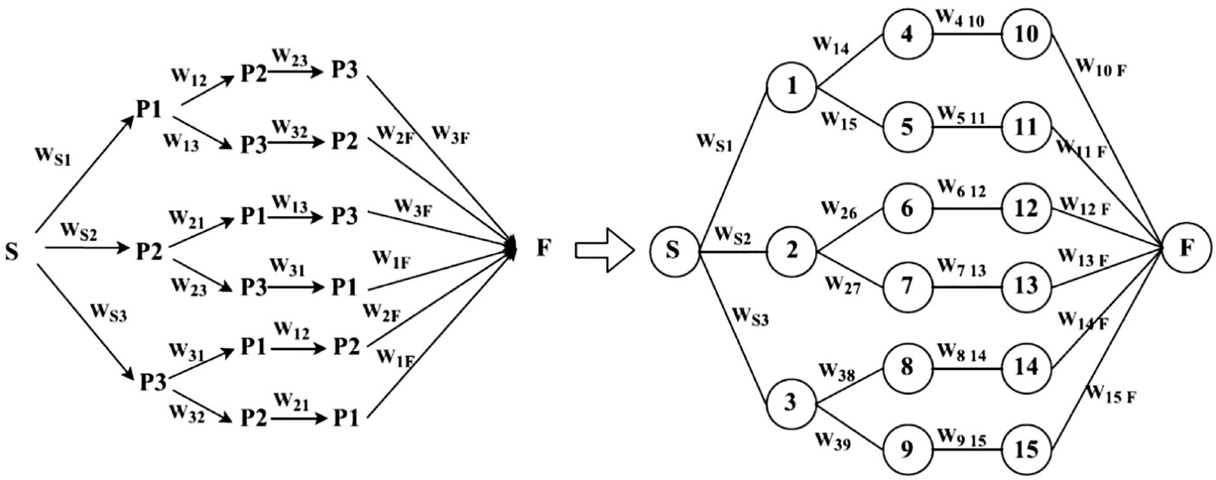

Fig. 8. Potential transport schedule to graph.

Finally, those models were packaged by ArcGIS Pro and published or shared in ArcGIS online to be used by the web application.

Apart from the 3D model transformation from BIM environment to GIS environment, the proposed system also has functionalities such as optimizing lift operation and vessel transport schedule. The optimization algorithms were realized in JavaScript and embedded into the integrated BIM/GIS system. The developed functions include retrieving information from BIM model and GIS spatial data, optimizing module layouts on each vessel, and obtaining the optimal transport schedule for each vessel. With the developed BIM/GIS-based system, not only the required information (e.g., module dimensions, weight, and platform locations) can be extracted automatically and efficiently, but also the module layout on each vessel and vessel transport schedule.

4. Illustrative example

4.1. Example introduction

An example is herein used to illustrate the proposed optimization approach and system. In the example, there are three offshore platforms with eighteen modules and two vessels are used to transport all the disassembled modules to a site factory on land. The overview of the three offshore platforms, two vessels, and factory location is presented in the developed BIM/GIS-based web system (see Fig. 11). In addition, an interface integrated with developed functions (i.e. information extraction, module layout optimization, and vessel transport schedule optimization) for topsides disassembly planning is also presented in Fig. 12.

4.2. Demonstration of the developed system for lift planning among multiple offshore platforms

With the developed system, first, the information required for module layout optimization can be extracted by clicking the button '*Information Extraction*'. The extracted information includes the module location, module weight, and predefined area positions (see Fig. 11(a)). Then, with the obtained information, the button '*Module Layout Optimization*' can be used to optimize module layouts on each vessel and the 2D view of the module layout on each vessel can be visualized as shown in Fig. 11(b). M_{ij} represents the *jth* module on *ith* offshore platform and should be lifted to the predefined location as illustrated in the optimized results. Since three heuristic algorithms have been implemented and compared in this study, the comparison and selection of optimal algorithm, which was finally used to develop the '*Module Layout Optimization*' button, are introduced in Section 4.3. Finally, based on the optimized module layout, the optimal vessel transport schedule can be obtained using button '*Transport Schedule Optimization*'. Schedule clash detection is conducted simultaneously. The final vessel transport schedule can also be visualized as shown in Fig. 11(c). Within the developed web system, information extraction and optimization are automatically conducted and the optimized results show that the proposed system can improve the efficiency of topsides disassembly planning among multiple offshore platforms.

4.3. Algorithm selection for module layout optimization

In addition to obtaining the optimized module layout on vessels and vessel transport schedule of the used illustrative example, the algorithms used for each optimization are also compared. Fig. 13. shows the

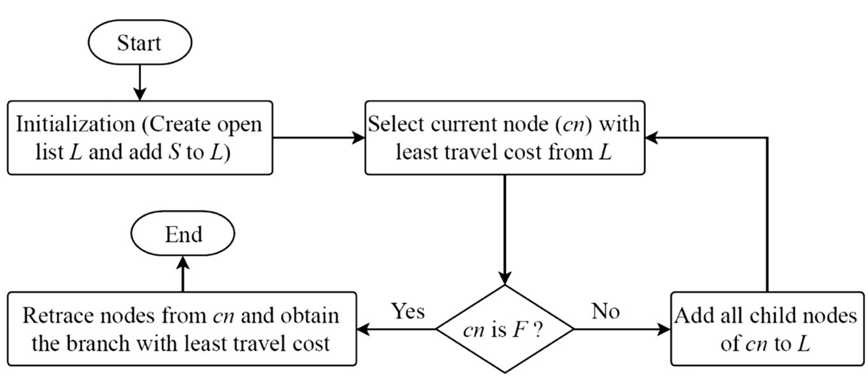

Fig. 9. Flowchart of graph search technique.

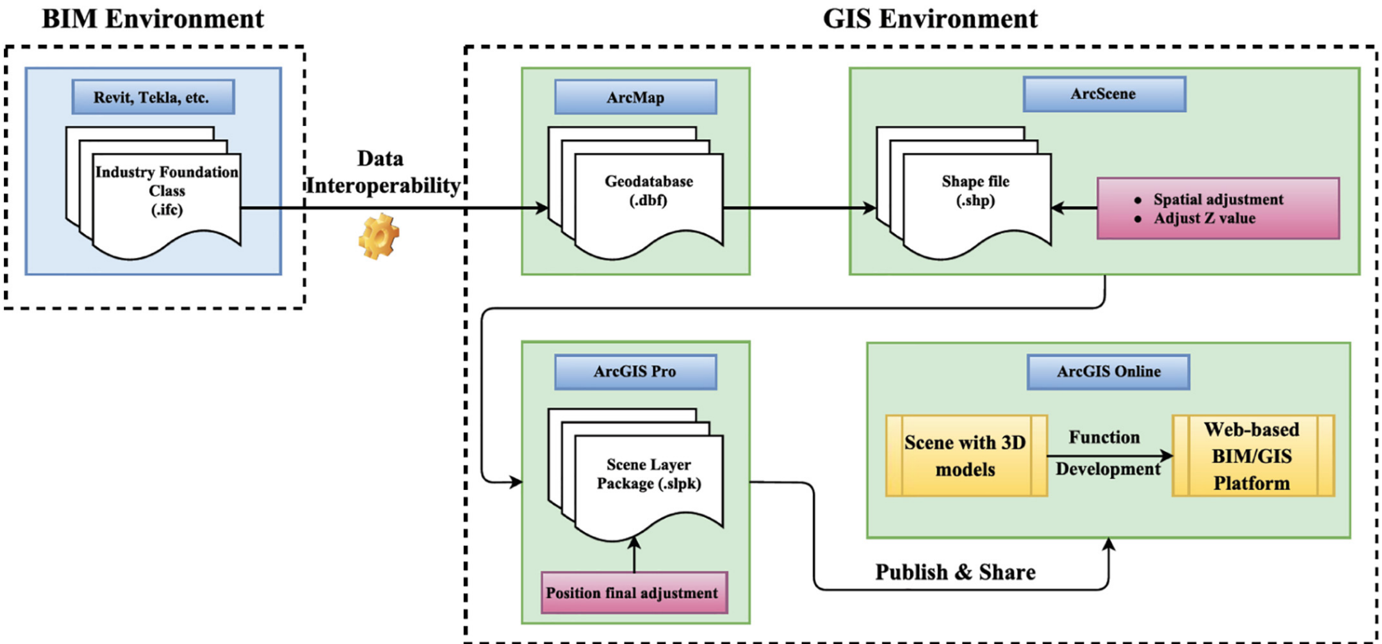

Fig. 10. Workflow of web-based BIM/GIS system development.

performance comparison among GA, PSO, and FA when optimizing the module layout on vessels. The convergence speed of these three algorithms with different population size (30 or 50 or 80) is presented in Fig. 13(a). According to convergence lines, FA can reach the global optima with only a few generations whatever the population size is. As for PSO and GA, more generations are required to obtain the global best and GA requires the most generations. The reason that FA is more efficient is FA divides the whole population into subgroups automatically,

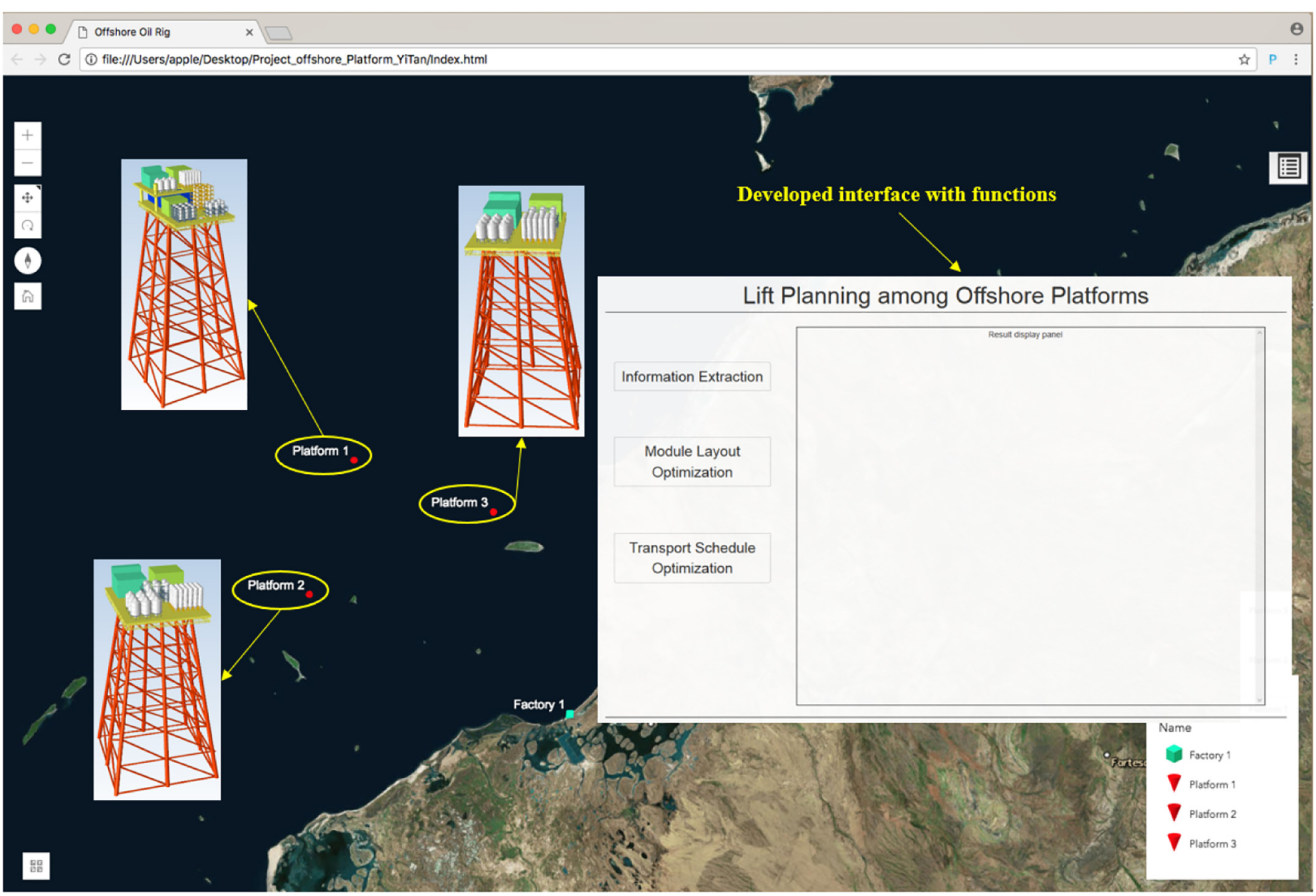

Fig. 11. Overview of the illustrative example in developed system.

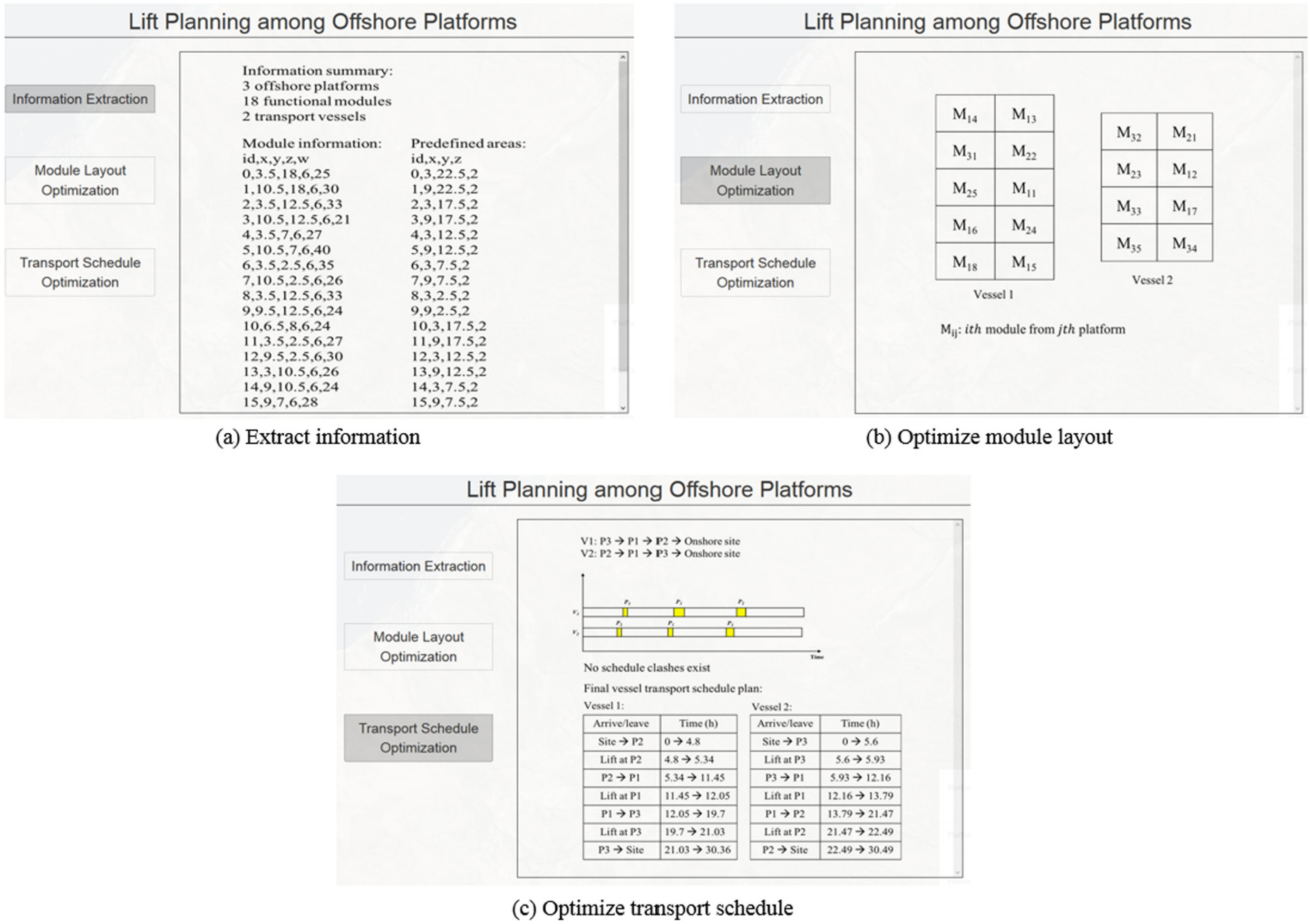

Fig. 12. BIM/GIS-based web system demonstration.

and each group can swarm around each local optima. Among all these local optima, the global optima can be found efficiently. In addition, such subdivisions allow fireflies to be able to find all local optima simultaneously if the population size is higher than the number of subgroups, which can be reflected in Fig. 13(b), where FA converges faster with bigger population size. However, both GA and PSO are not very sensitive to population size in this study. Although PSO and FA are continuing techniques that are originally more suitable for solving continues problems rather than combinational problems and GA is initially discrete technique that is more suitable for combinational problems like QAP, with properly transformation, discrete problems can be mapped into continues representation and then efficiently optimized with PSO and FA. Therefore, FA is finally recommended as the algorithm for optimizing module layout on vessels.

4.4. System evaluation

According to the results of the illustrative example, the developed system can well assist lift planning of topsides disassembly among multiple offshore platforms. Especially, the proposed method of addressing the module layout planning varies from the traditional QAP. In this study, the optimization objective focuses on the minimizing the total offshore heavy lift time, which can significantly reduce the offshore safety problems, rather than minimizing the material flow or handle cost among facilities after assignment. Therefore, the developed system can help address similar assignment problems, where the assigning process requires careful consideration. In addition, the comparison of the three heuristic algorithms well identifies the optimal algorithm, namely firefly algorithm, from the commonly used heuristic algorithms to solve the assignment problem mentioned above. Analysis of the impact of different population size on algorithm performance can assist adjusting parameters to further improve the efficiency of the selected algorithm. Finally, the approach proposed in this study to integrate BIM and GIS, providing an efficient and accurate information hub for the developed system, is easier to realize compared to previous BIM-GIS integration studies.

However, the developed BIM/GIS-based web system has some limitations. For example, although BIM and GIS have been integrated, manual adjustments on 3D models during file format conversion are complicated and time-consuming. Such integration process has to be conducted for every new multiple offshore platform decommissioning project. To improve the efficiency and accuracy of the developed web-based platform, the integration process of BIM and GIS should be automated. The ideal BIM/GIS-based web system is expected to use IFC file directly without any model position and scale adjustments, which is one future direction of this study.

5. Conclusions

This paper formulated the module layout and vessel transport schedule optimization problems and developed a BIM/GIS-based web system to assist lift planning among multiple offshore platforms when disassembling their topsides. Lift planning includes optimizing module layout on vessels and vessel transport schedule among platforms. BIM technology was used to provide all required information for module layout optimization, while GIS was used to provide necessary spatial

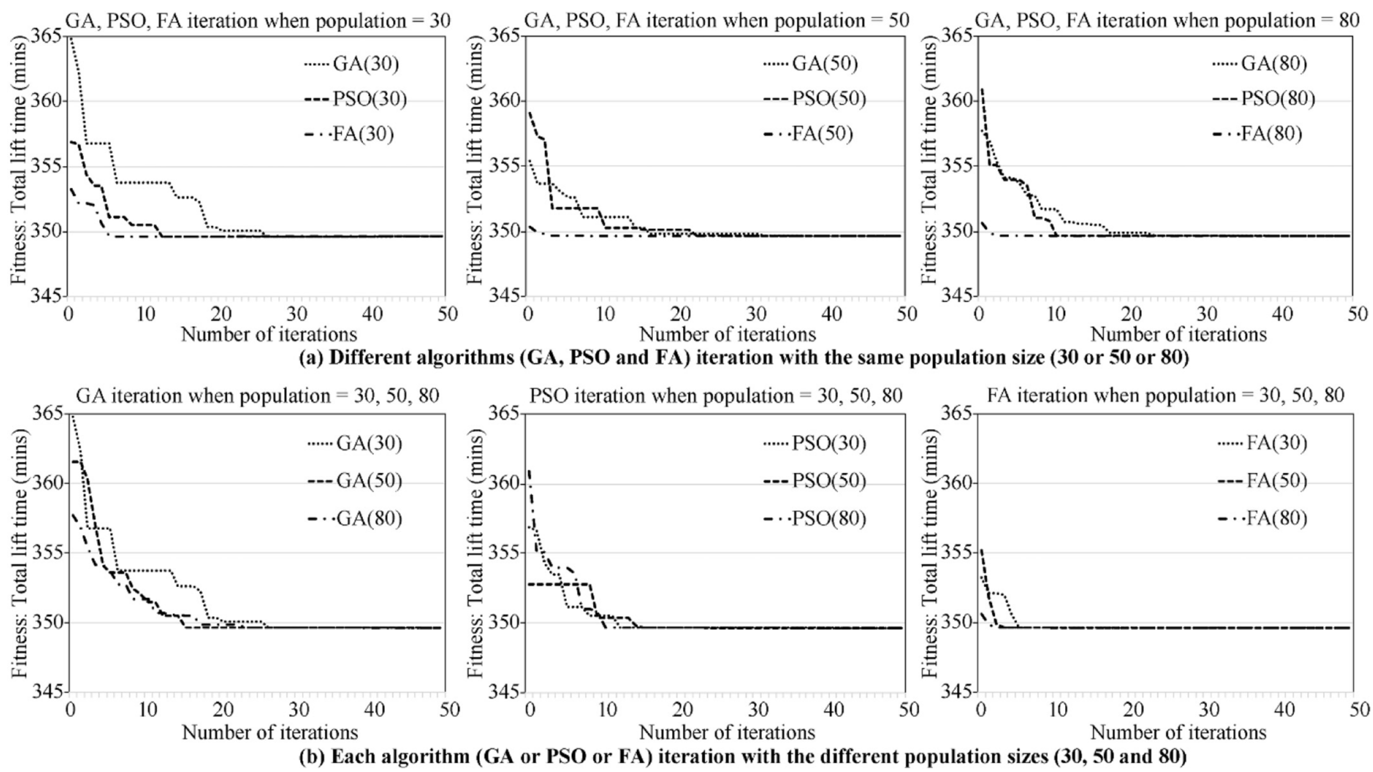

Fig. 13. Performance comparison of GA, PSO, and FA.

information for vessel transport schedule optimization. GA, PSO, and FA were implemented and compared to obtain the optimal module layout with the minimum total lift time. Graph search technique and schedule clash detection method were used to obtain vessel transport schedule with the minimum offshore sailing time. In addition, the proposed approach of integrating BIM and GIS in this study is economical and easy to implement. An example of three offshore platforms with eighteen functional modules in total was used to illustrate the developed web system. Results show that the practical efficiency of lift planning among multiple offshore platforms can be significantly improved by the developed BIM/GIS-based web system compared with the current experience-based approach. In addition to assisting decision-making on topsides disassembly, the developed BIM/GIS-based web system can also be applied to other fields such as resource allocation among multiple construction sites and maintenance task assignment among multiple buildings in a public area like a school campus. The implemented population-based algorithms (GA, PSO, and FA), can also be adjusted to solve other facility layout planning problems in fields such as manufacturing factories and construction sites.

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References

[1] Economic Report, Oil & Gas UK, Available at: http://oilandgasuk.co.uk/wp-content/uploads/2015/05/EC038.pdf, (2013) (Accessed on date 6-1-2018).
[2] M. Henrion, B. Bernstein, S. Swamy, A multi-attribute decision analysis for decommissioning offshore oil and gas platforms, Integr. Environ. Assess. Manag. 11 (4) (2015) 594–609 https://doi.org/10.1002/ieam.1693.
[3] N.A.W.A. Zawawi, M. Liew, K. Na, Decommissioning of offshore platform: a sustainable framework, Humanities, Science and Engineering (CHUSER), IEEE Colloquium, 2012, pp. 26–31 https://doi.org/10.1109/CHUSER.2012.6504275.
[4] J.C.P. Cheng, Y. Tan, Y. Song, X. Liu, X. Wang, A semi-automated approach to generate 4D/5D BIM models for evaluating different offshore oil and gas platform decommissioning options, Vis. Eng. 5 (1) (2017) 12 https://doi.org/10.1186/s40327-017-0053-2.
[5] T. Wang, J. Wang, P. Wu, J. Wang, Q. He, X. Wang, Estimating the environmental costs and benefits of demolition waste using life cycle assessment and willingness-to-pay: a case study in Shenzhen, J. Clean. Prod. 172 (2018) 14–26 https://doi.org/10.1016/j.jclepro.2017.10.168.
[6] Y. Tan, Y. Song, X. Liu, X. Wang, J.C. Cheng, A BIM-based framework for lift planning in topsides disassembly of offshore oil and gas platforms, Autom. Constr. 79 (2017) 19–30 https://doi.org/10.1016/j.autcon.2017.02.008.
[7] LOGGS Satellites Vulcan UR, Viscount VO, Vampire OD & Associated Infield Pipelines, ConocoPhillips (U.K.) Limited, 2017 GOV. UK. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/642126/LDP1_Decommissioning_Programmes.pdf (Accessed on date 16-1-2018).
[8] Audrey Decommissioning Programmes, Centrica North Sea Limited, 2017 GOV.UK. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/642131/Audrey_Decommissioning_Programmes.pdf (Accessed on date 16-1-2018).
[9] Saturn (Annabel) Decommissioning Programmes, Centrica North Sea Limited, 2017 GOV.UK. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/642130/Saturn_Annabel_Decommissioning_Programmes.pdf (Accessed on date 16-1-2018).
[10] J.A. Bondy, U.S.R. Murty, Graph theory with applications, (1976) (ISBN: 0-444-19451-7).
[11] R.J. Wilson, Introduction to Graph Theory, Longman Group Ltd (1996) (0-582-24993-7).
[12] J.L. Gross, J. Yellen, P. Zhang, Handbook of Graph Theory, CRC Press, 2013 (ISBN: 978-1-4398-8019-7).
[13] N. Deo, Graph Theory with Applications to Engineering and Computer Science, Courier Dover Publications, 2017 (ISBN: 0-486-80793-2).
[14] A. Kusiak, S.S. Heragu, The facility layout problem, Eur. J. Oper. Res. 29 (3) (1987) 229–251 https://doi.org/10.1016/0377-2217(87)90238-4.
[15] S.P. Singh, R.R. Sharma, A review of different approaches to the facility layout problems, Int. J. Adv. Manuf. Technol. 30 (5–6) (2006) 425–433 https://doi.org/10.1007/s00170-005-0087-9.
[16] A. Drira, H. Pierreval, S. Hajri-Gabouj, Facility layout problems: a survey, Annu. Rev. Control. 31 (2) (2007) 255–267 https://doi.org/10.1016/j.arcontrol.2007.04.001.
[17] A. Ramkumar, S. Ponnambalam, Hybrid ant colony system for solving quadratic assignment formulation of machine layout problems, IEEE Conference on Cybernetics and Intelligent Systems, Bangkok, Thailand, 2006, pp. 1–5 https://doi.org/10.1109/ICCIS.2006.252286.
[18] A. Shukla, A modified bat algorithm for the quadratic assignment problem, IEEE Congress on Evolutionary Computation (CEC), Sendai, Japan, 2015, pp. 486–490 https://doi.org/10.1109/CEC.2015.7256929.
[19] R.E. Burkard, Quadratic assignment problems, Eur. J. Oper. Res. 15 (3) (1984) 283–289 https://doi.org/10.1016/S0304-0208(08)73232-8.

[20] D.M. Tate, A.E. Smith, A genetic approach to the quadratic assignment problem, Comput. Oper. Res. 22 (1) (1995) 73–83 https://doi.org/10.1016/0305-0548(93)E0020-T.
[21] H. Li, P.E. Love, Site-level facilities layout using genetic algorithms, J. Comput. Civ. Eng. 12 (4) (1998) 227–231 https://doi.org/10.1061/(ASCE)0887-3801(1998)12:4(227).
[22] R.K. Ahuja, J.B. Orlin, A. Tiwari, A greedy genetic algorithm for the quadratic assignment problem, Comput. Oper. Res. 27 (10) (2000) 917–934 https://doi.org/10.1016/S0305-0548(99)00067-2.
[23] U. Tosun, A new recombination operator for the genetic algorithm solution of the quadratic assignment problem, Procedia Comput. Sci. 32 (Supplement C) (2014) 29–36 https://doi.org/10.1016/j.procs.2014.05.394.
[24] S. Tsutsui, N. Fujimoto, Solving quadratic assignment problems by genetic algorithms with GPU computation: a case study, Proceedings of the 11th Annual Conference Companion on Genetic and Evolutionary Computation Conference: Late Breaking Papers, ACM, 2009, pp. 2523–2530 https://doi.org/10.1145/1570256.1570355.
[25] C. Lv, H. Zhao, X. Yang, Particle swarm optimization algorithm for quadratic assignment problem, Proceedings of International Conference on Computer Science and Network Technology (ICCSNT), 2011, pp. 1728–1731 https://doi.org/10.1109/ICCSNT.2011.6182302.
[26] T. Gong, A.L. Tuson, Particle swarm optimization for quadratic assignment problems-a forma analysis approach, Int. J. Comput. Intell. Res. 4 (2) (2008) 177–185. Available at: https://pdfs.semanticscholar.org/fe9c/428be67c84e0e01cbc519de620823945338a.pdf (Accessed on date 16-1-2018).
[27] H. Liu, A. Abraham, M. Clerc, An hybrid fuzzy variable neighborhood particle swarm optimization algorithm for solving quadratic assignment problems, J. Univ. Comput. Sci. 13 (9) (2007) 1309–1331. Available at: http://www.jucs.org/jucs_13_9/an_hybrid_fuzzy_variable/jucs_13_9_1309_1331_liu.pdf (Accessed on date 16-1-2018).
[28] M. Zhao, A. Abraham, C. Grosan, H. Liu, A fuzzy particle swarm approach to multiobjective quadratic assignment problems, Proceedings of Second Asia Modeling & Simulation, 2008, pp. 516–521 https://doi.org/10.1109/AMS.2008.169.
[29] X.-S. Yang, Firefly algorithm, stochastic test functions and design optimisation, Int. J. Bio-Inspired Comput. 2 (2) (2010) 78–84 https://doi.org/10.1504/IJBIC.2010.032124.
[30] X.-S. Yang, Firefly algorithm, Levy flights and global optimization, Research and Development in Intelligent Systems XXVI, Springer, 2010, pp. 209–218 https://doi.org/10.1007/978-1-84882-983-1_15.
[31] X.-S. Yang, Firefly algorithms for multimodal optimization, International Symposium on Stochastic Algorithms, Springer, 2009, pp. 169–178 https://doi.org/10.1007/978-3-642-04944-6_14.
[32] X.-S. Yang, Nature-inspired Metaheuristic Algorithms, Luniver Press, 2010 (ISBN-13:978-905986-28-6).
[33] K. Durkota, Implementation of a Discrete Firefly Algorithm for the QAP Problem Within the Sage Framework, Bachelor Thesis Czech Technical University, 2011 Available at: http://agents.fel.cvut.cz/~durkota/files/BachelorThesisDurkota.pdf (Accessed on date 16-1-2018).
[34] I. Fister Jr., X.-S. Yang, I. Fister, J. Brest, Memetic Firefly Algorithm for Combinatorial Optimization, arXiv preprint arXiv:1204.5165 (2012).
[35] E.L. Lawler, J.K. Lenstra, A.R. Kan, D.B. Shmoys, The Traveling Salesman Problem: A Guided Tour of Combinatorial Optimization, Wiley, New York, 1985 (ISBN: 978-0471904137).
[36] K.L. Hoffman, M. Padberg, G. Rinaldi, Traveling salesman problem, Encyclopedia of Operations Research and Management Science, Springer, Boston, MA, 2013, pp. 1573–1578 https://doi.org/10.1007/978-1-4419-1153-7_1068.
[37] W.R. Stewart, Chinese postman problem, Encyclopedia of Operations Research and Management Science, Springer, Boston, MA, 2013, pp. 161–164 https://doi.org/10.1007/978-1-4419-1153-7_110.
[38] R. Volk, J. Stengel, F. Schultmann, Building Information Modeling (BIM) for existing buildings — literature review and future needs, Autom. Constr. 38 (0) (2014) 109–127 https://doi.org/10.1016/j.autcon.2013.10.023.
[39] Y. Song, Y. Ge, J. Wang, Z. Ren, Y. Liao, J. Peng, Spatial distribution estimation of malaria in northern China and its scenarios in 2020, 2030, 2040 and 2050, Malar. J. 15 (1) (2016) 345 https://doi.org/10.1186/s12936-016-1395-2.
[40] Y. Song, X. Wang, G. Wright, D. Thatcher, P. Wu, P. Felix, Traffic volume prediction with segment-based regression kriging and its implementation in assessing the impact of heavy vehicles, IEEE Trans. Intell. Transp. Syst. (99) (2018) 1–12 https://doi.org/10.1109/TITS.2018.2805817.
[41] Y. Song, X. Wang, Y. Tan, P. Wu, M. Sutrisna, J. Cheng, K. Hampson, Trends and opportunities of BIM-GIS integration in the architecture, engineering and construction industry: a review from a spatio-temporal statistical perspective, ISPRS Int. J. Geo-Information 6 (12) (2017) 397 https://doi.org/10.3390/ijgi6120397.
[42] T. Wang, T. Krijnen, B. De Vries, Combining GIS and BIM for facility reuse: a profiling approach, Res. Urbanism Ser. 4 (2016) 185–203 https://doi.org/10.7480/rius.4.824.
[43] T.W. Kang, C.H. Hong, A study on software architecture for effective BIM/GIS-based facility management data integration, Autom. Constr. 54 (2015) 25–38 https://doi.org/10.1016/j.autcon.2015.03.019.
[44] R. Liu, R. Issa, 3D visualization of sub-surface pipelines in connection with the building utilities: integrating GIS and BIM for facility management, Comput. Civ. Eng. (2012) 341–348 https://doi.org/10.1061/9780784412343.0043.
[45] C. Mignard, C. Nicolle, Merging BIM and GIS using ontologies application to urban facility management in ACTIVe3D, Comput. Ind. 65 (9) (2014) 1276–1290 https://doi.org/10.1016/j.compind.2014.07.008.
[46] J.C. Cheng, Y. Deng, An integrated BIM-GIS framework for utility information management and analyses, Comput. Civ. Eng. 2015 (2015) 667–674 https://doi.org/10.1061/9780784479247.083.
[47] W. Wu, X. Yang, Q. Fan, GIS-BIM based virtual facility energy assessment (VFEA)–framework development and use case of California State University, Fresno, Comput. Civ. Build. Eng. (2014) 339–346 https://doi.org/10.1061/9780784413616.043.
[48] S. Niu, W. Pan, Y. Zhao, A BIM-GIS integrated web-based visualization system for low energy building design, Procedia Eng. 121 (Supplement C) (2015) 2184–2192 https://doi.org/10.1016/j.proeng.2015.09.091.
[49] S. Yamamura, L. Fan, Y. Suzuki, Assessment of urban energy performance through integration of BIM and GIS for smart city planning, Procedia Eng. 180 (Supplement C) (2017) 1462–1472 https://doi.org/10.1016/j.proeng.2017.04.309.
[50] J. Shi, P. Liu, An agent-based evacuation model to support fire safety design based on an integrated 3D GIS and BIM platform, Comput. Civ. Build. Eng. 2014 (2014) 1893–1900 https://doi.org/10.1061/9780784413616.235.
[51] Y. Deng, J.C. Cheng, C. Anumba, A framework for 3D traffic noise mapping using data from BIM and GIS integration, Struct. Infrastruct. Eng. (2016) 1–14 https://doi.org/10.1080/15732479.2015.1110603.
[52] J. Irizarry, E.P. Karan, Optimizing location of tower cranes on construction sites through GIS and BIM integration, Electron. J. Inf. Technol. Constr. 17 (2012) 361–366 http://www.itcon.org/2012/23.
[53] T. Park, T. Kang, Y. Lee, K. Seo, Project cost estimation of national road in preliminary feasibility stage using BIM/GIS platform, Comput. Civ. Build. Eng. (2014) 423–430 https://doi.org/10.1061/9780784413616.053.
[54] H. Kim, Z. Chen, C.-S. Cho, H. Moon, K. Ju, W. Choi, Integration of BIM and GIS: highway cut and fill earthwork balancing, International Workshop on Computing in Civil Engineering, 2015 https://doi.org/10.1061/9780784479247.058.
[55] J. Irizarry, E.P. Karan, F. Jalaei, Integrating BIM and GIS to improve the visual monitoring of construction supply chain management, Autom. Constr. 31 (Supplement C) (2013) 241–254 https://doi.org/10.1016/j.autcon.2012.12.005.
[56] S. Amirebrahimi, A. Rajabifard, P. Mendis, T. Ngo, A BIM-GIS integration method in support of the assessment and 3D visualisation of flood damage to a building, J. Spat. Sci. (2016) 1–34 https://doi.org/10.1080/14498596.2016.1189365.
[57] H. Du, J. Du, S. Huang, GIS, GPS, and BIM-based risk control of subway station construction, Proceedings of the 5th International Conference on Transportation Engineering, Guangzhou, China, 2015, pp. 1478–1485 https://doi.org/10.1061/9780784479384.186.
[58] E.P. Karan, J. Irizarry, J. Haymaker, BIM and GIS integration and interoperability based on semantic web technology, J. Comput. Civ. Eng. 30 (3) (2015), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000519.
[59] A.-H. Hor, A. Jadidi, G. Sohn, BIM-GIS integrated geospatial information model using semantic web and RDF graphs, ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences, 3 2016 (4). Available at: https://www.isprs-ann-photogramm-remote-sens-spatial-inf-sci.net/III-4/73/2016/isprs-annals-III-4-73-2016.pdf (Accessed on date 16-1-2018).
[60] Y. Tan, J.C.P. Cheng, X. Liu, Y. Song, X. Wang, A BIM-based framework for lifting planning in disassembly of offshore oil and gas platforms, Proceedings of International Conference on Innovative Production and Construction, Perth, Australia, 2016, p. 96 http://repository.ust.hk/ir/Record/1783.1-81184.
[61] J.C.P. Cheng, Y. Tan, Y. Song, Z. Mei, V.J.L. Gan, X. Wang, Developing an evacuation evaluation model for offshore oil and gas platforms using BIM and agent-based model, Autom. Constr. 89 (2018) 214–224 https://doi.org/10.1016/j.autcon.2018.02.01.