Sensors and Materials, Vol. 35, No. 4 (2023) 1375–1384
MYU Tokyo

S & M 3253

Optimal Path Planner of Training Course Recommendation for Reskilling/Upskilling in New S-curve Industries

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(Received November 28, 2022; accepted February 14, 2023)

Keywords: graph-based planner, path planning, new S-curve industries, training, course recommendation

To meet the need for a more skilled and technology-oriented workforce, the new S-curve industrial revolution is restructuring the labor market worldwide. The Thai government is now focusing on upgrading the country's human resource skills to meet new demands. This paper presents an application of the well-known A* path planner in the field of artificial intelligence (AI) for recommending reskilling/upskilling training courses. Data are obtained from the Career Discovery Analysis Platform (CDAP), which was designed and implemented by the authors. The results obtained from CDAP are then summarized, leading to training course recommendations for the government and individuals. By considering the mean score zone as the sensing node of a graph-based planner, an optimal path for upskilling training course recommendation can be identified.

1. Introduction

In recent years, the Thai government has committed itself to following the so-called Thailand 4.0 Model, which, in contrast to the traditional model characterized by an agriculture-based economy with intensive labor and low levels of trading, places more emphasis on achieving local economic growth and sustainable development goals.(1) Thus, this model strikes a balance between the local economy and the global economy. The new S-curve industries, which include aviation, logistics, biofuels, biochemicals, digital technology, medical hubs, and robotics, have arisen in the Thai digital environment as a result of the adoption of the Thailand 4.0 Model and the digital economy development plan.(1)

The Thai government also adopted a number of supporting policies to encourage new business owners to launch new businesses in the new S-curve industries. However, given that highly technical workers usually possess in-depth and specialized knowledge,(2) which is essential to meet the demands of these industries, the current situation is creating a significant human resources challenge for traditional organizations. Many other organizations have been compelled to adopt technology to fill their job openings owing to the sharp decline in the application pool resulting from the increased requirement for skilled workers. Because of

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https://doi.org/10.18494/SAM4261

ISSN 0914-4935

heightened competition for talented workers, organizations in the emerging S-curve industries face the same difficulties when trying to fill open positions with qualified applications.

During the COVID-19 pandemic, the need for contactless substitutes drove the widespread acceptance of digital technology and the growth in the number of businesses providing branchless banking, customizable insurance, contactless payment systems,(3) and other forms of digital transformation to manage the organization of workforces.(4) Thus, the pandemic helped accelerate the implementation of a digital environment. From the perspective of the retooling framework, the pandemic opened new research topics on using tools in computational intelligence (CI) and artificial intelligence (AI).(5–10) The disruption of demand caused by digital-communication-based technology such as big data, cloud computing, and the Internet of Things (IoT) led to the emergence of a new chapter not only in industrial technology but also in human resources (HR), namely, the 4.0 generation.(5–11)

With the above disruption and acceleration both from the new era of digital technology and from the recent pandemic, human resources development (HRD) faces a new challenge in coping with its prime imperative. Many aspects of HRD(12–18) may require the redesign of key elements of its functions and models to upgrade leadership capabilities, reskill/upskill workers, and validate frameworks and tools. These issues raise the need for enhanced solutions to meet these new demands.

From the perspective of selecting training programs, decision making has traditionally been based on human judgement, which may not be optimal if many choices are available. We demonstrate how to use the A* algorithm as an HRD tool for the decision making and planning of reskilling/upskilling programs. To be specific, a new application of the well-known A* path planner in the field of AI is applied to search for the optimal path to generate reskilling/upskilling training course recommendations. A* graph-based planners are briefly reviewed in Sect. 2. In Sect. 3, the collection of data and patterns of individual test scores using the Career Discovery Analysis Platform (CDAP) is discussed, leading to a method for executing the optimal planner. Section 4 provides results and Sect. 5 gives concluding remarks.

2. A* Graph-based Planners

We outline the motivation for using AI in HR analytics(19–21) before presenting a brief review of graph-based planners using the A* algorithm. Human resource management plays an important role in employee retention to help achieve an organization's objectives. It is crucial for organizations to retain their valuable employees to ensure their survival. Since the recruitment and retention of staff play an important role in ensuring suitable conditions for employee performance, the evaluation of individuals is essential to determine how well organizations perform.(18)

A brief review of the A* graph search algorithm follows. The algorithm is applied to path planning for reskilling/upskilling training. The initial node is the initial skill, the goal node is the new desired set of skills to be acquired, and the path between the two nodes can be computed using graph search algorithms. One may ask why a path must be generated since a training course can be offered to achieve the goal. The reason is that since the COVID-19 pandemic, training has had various alternatives, namely, online, on-site, or hybrid training, for reasons of healthcare or cost-effectiveness. The combination of different courses, contents, and types of training correspond to different paths in the algorithm.

Graph search algorithms have been used in networks and routing problems and are well understood in computer science and engineering. Many of these algorithms require the calculation cost of visiting each node of the graph to determine the shortest path between the initial and goal nodes. Visiting every node may be computationally expensive for a highly connected graph. The A* search algorithm is a method for computing optimal paths that is derived from the A search method. To convert the A search algorithm to the optimal A* algorithm, the search is started at the initial node, and then the path is navigated optimally through the graph to the goal node. The search generates the optimal path incrementally, updates the new alternative path, considers the nodes that could be added to the path, and chooses the best nodes. The formula for measuring the plausibility of a node can be expressed as

$$J(i) = K(i) + L(i), \tag{1}$$

where $J(i)$ is a measure of the advantageousness of a move to node i, $K(i)$ the cost of reaching node i from the initial node, and $L(i)$ the lowest cost of the path from node i to the goal.

Figure 1 provides an overview of the proposed paradigm for searching for the optimal training path for reskilling/upskilling course recommendations. A person at the Start block must take tests from CDAP (see Sect. 3.1) and must finish the new S-curve test (orange decision block) to obtain a policy recommendation. When the person finishes the test, a score is automatically generated and plotted as a dot on the graph shown in Sect. 3.2. Then the score is transformed into a position represented by a node on the network circuit. A node represents a recommended course for upskilling/reskilling. Upon knowing the position of the starting node, the A* algorithm can be applied to generate the optimal path for achieving the goal. A pseudocode for the A* algorithm that also gives an explanation of the algorithm is presented in Table 1.

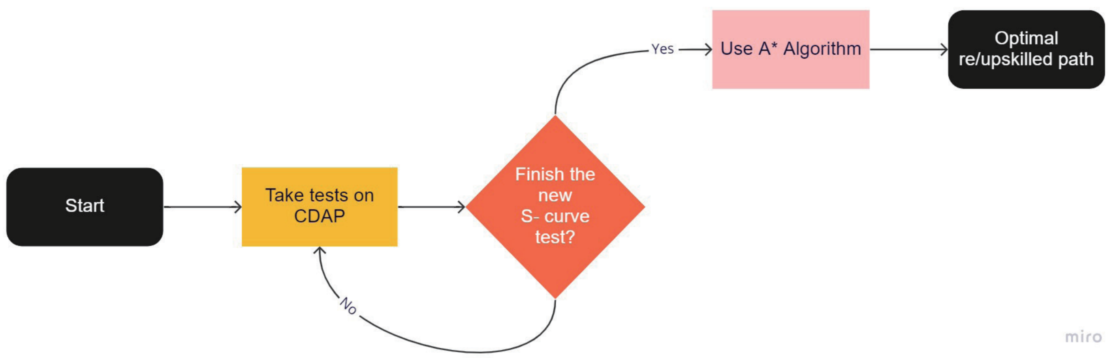


Fig. 1. (Color online) Simple flow diagram illustrating concept of applying A* algorithm in this study.

Table 1
Pseudocode for A* algorithm.

```
Initialization: StartNode and EndNode
        Set K = 0 as cost value of the StartNode
Main Step:
        1)  Create NotVisited as an opened list or array and Visited as a closed list or array
        2)  Add StartNode in the NotVisited list
        3)  Start a while loop then run (See Subroutine (3))
        4)  Reiterate Step 3) until length of NotVisited = 0.
Subroutine (3):
        A.  Set CurrentNode to NotVisited
        B.  Start a for loop with NotVisited list (See Psuedo-code_Subroutine (3.B))
        C.  Remove CurrentNode from NotVisited list
        D.  Add CurrentNode to Visited list
        E.  If position of CurrentNode = position of EndNode
              Then Set EndNode = CurrentNode
              And
              Return the ResultPath
              End of loop
            Else continue to loop the nodes
        F.  Start a for loop with the neighbors of CurrentNodes (See Subroutine (3.F))
Subroutine (3.B):
            If Node_J < CurrentNode_J or
              Node_J = CurrentNode_J and Node_L < CurrentNode_L
              Then Set CurrentNode to Node_J
Subroutine (3.F):
        (a) Ignore the nodes that are unreachable
        (b) Calculate the new K cost of each neighbor node;
            CurrentNode_K + Cost(CurrentNode, NeighborNode)
        (c) If new K cost value < K cost value of NeighborNode
              or the NeighborNode is not in the NotVisited list
              Then Define and Update the J, K, L costs of the NeighborNode and
              Set the node ancestors or parent NeighborNode to CurrentNode
              Then check
              If NeighborNode is not in the NotVisited list
              Then Add this NeighborNode to the NotVisited list
```

For details of the calculation and derivation of the A* algorithm and examples of its use for general purposes, see Ref. 22; the purpose of this section is to review this well-known and widely used algorithm for obtaining the optimal distance cost function or searching for an optimal path. In this study, the algorithm is used to search for the optimal training path for reskilling/upskilling course recommendations, as discussed in Sect. 4.

3. Data Patterns from CDAP

3.1 General information about CDAP

CDAP is a web-based platform that helps users discover a suitable career for themselves. The platform consists of five tests: the career interest test, skill test, work and value test, personality test, and new S-curve test. In other words, CDAP is a platform for guidance, job recruiting, and career development, with a focus on Thai students and people working in an era in which the world of work has changed radically. The platform was constructed to prepare and train students, mentors, working people, and other interested parties to learn and use it for self-guided and professional development. The platform was designed, developed, and finally deployed, and has been in use for two years. More than 10000 people in Thailand have used CDAP, whose use is free of charge and is available in the Thai language. The Department of Employment, Ministry of Labor of Thailand was one of the partners of the CDAP project. Figure 2 shows an image from the homepage of the CDAP website (www.cdapthailand.com).

3.2 Data patterns for policy recommendation

One feature of CDAP is that it provides policy recommendations for policy makers and researchers involved in designing courses for the upskilling and reskilling of workers currently working or desiring to work in the new S-curve industries. The data used for policy recommendation shown in Fig. 3 is collected from the test results of CDAP users. A dot represents a summary score of the new S-curve test. Each dot on the x–y plane can be recognized as a coordinate on the policy recommendation chart. From the perspective of training, the chart can be divided into various zones corresponding to different levels of desire and different perceptions regarding the opportunity to pursue a career in the new S-curve industries, which can be categorized and quantified into small, medium, and large industries. Training programs can then be designed and established to support an individual to achieve their goal, as shown in Fig. 4. By recognizing a training program or a course as a node (Fig. 5), the A* path planner can be employed by transforming zone-based training programs available to CDAP users into a graph. The next section provides an example of simulation results.

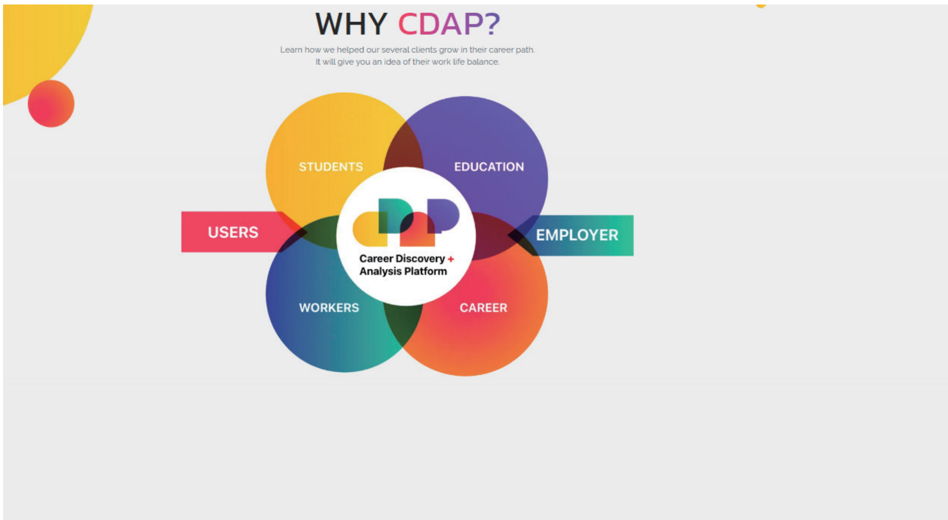


Fig. 2. (Color online) Image from homepage of CDAP website (www.cdapthailand.com).

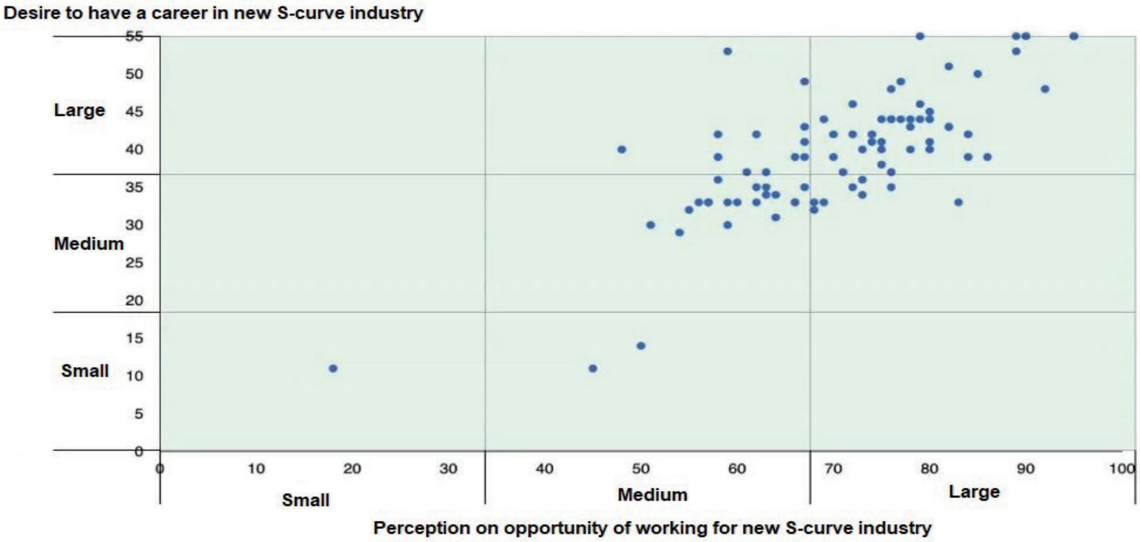


Fig. 3. (Color online) Data used for policy recommendation by CDAP (as of Nov 27, 2022). Source: www.cdapthailand.com.

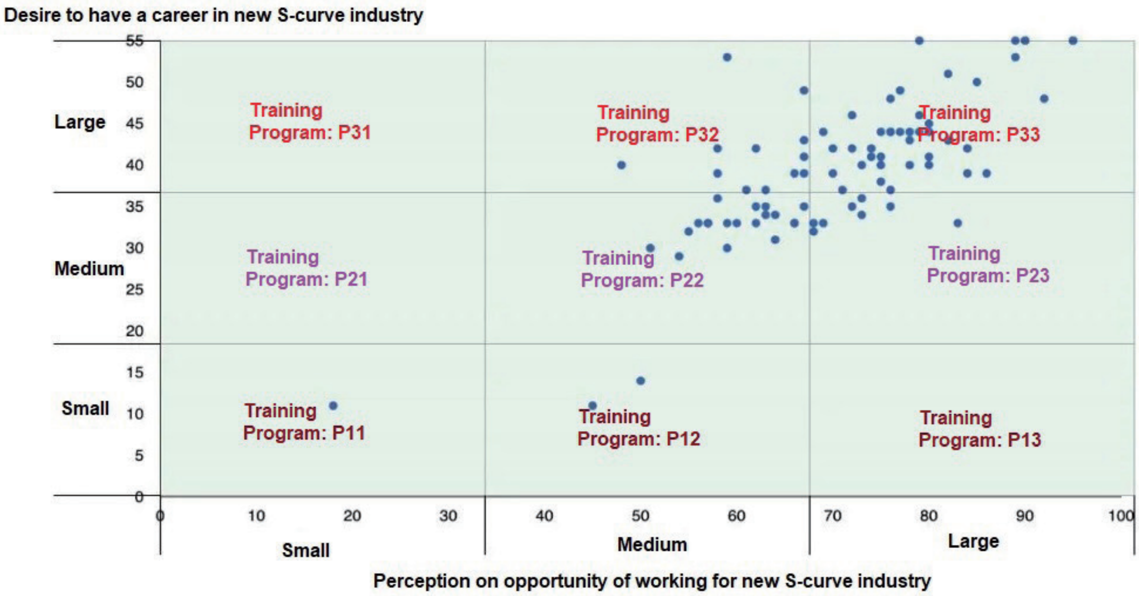


Fig. 4. (Color online) Zone-based recommendation of training programs for CDAP users.

4. Results

From Fig. 5, a rule base for generating training programs can be assigned for each training. In Fig. 6, the nodes are represented as goals, and the edges represent paths between two nodes, which have assigned costs, Cn, where n = 1, 2, 3, …, 16. Additional information can be attached to edges such as the direction of the training program. Paths can be computed between two

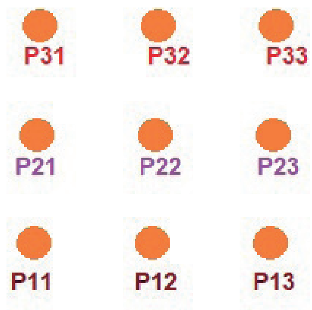
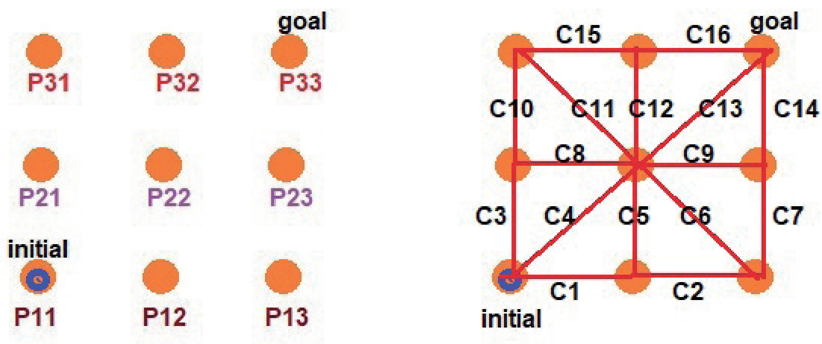


Fig. 5. (Color online) Recognition of training programs or courses as nodes.



(a) (b)

Fig. 6. (Color online) (a) Grid of training program possibilities. (b) Cost of each training.

points using standard graph algorithms such as the A search algorithm. The optimal path can be achieved by minimizing the cost using the A* algorithm from Sect. 2 with

$$J^*(i) = K^*(i) + L^*(i). \tag{2}$$

As shown in Fig. 6(b), the cost of the training program, Cn, depends on the type of training required. Many different types of training with greatly varying cost exist, such as online training, on-site training, a hybrid of the two, seminars, group workshops, one-to-one tutoring, and consultant training. Before choosing a type of training, it is desirable to know the results of completing the training to select a training program comprising activities that best fit the results with an appropriate cost of training. To meet the training cost Cn, a training budget should be included as a separate item in the yearly budget. The training budget should include the costs of the initial communication about the program, the training delivery and materials, the staff time, the instructor fee, travel and accommodation, the hiring of the venue, maintenance of the meeting room, meal expenses, time spent away from work, ongoing training, and contingencies.

For example, we consider the situation described in Fig. 6 and Table 2 with the aim of selecting the path with the minimum cost from P11 as the initial point to P33 as the goal point, Traditionally, from a quick visual inspection, one may choose the shortest path as the diagonal path from P11 to P33 passing through P22. For this path, the corresponding costs are C4 and C13, and the cost J would be 2500 + 6800 = 9300 Thai baht (THB). Alternatively, one may select a simple and lazy strategy of choosing the path along the horizontal line to the right vertex and vertically upward to the goal that passes through nodes P12, P13, and P23. The cost of choosing this training set with costs C1, C2, C7, and C14 would be $J = 2400 + 2600 + 3100 + 5200 = 13300$ THB.

In comparison, the optimal path can be obtained by using the A* algorithm and the cost information for each Cn shown in Table 2. It is easy to calculate that the optimal path for the recommendation is P11–P22–P32–P33 with costs C4, C12, and C16, giving an optimal cost J^* of 2500 + 2400 + 2000 = 6900 THB. This can be guaranteed by the admissibility condition in the A* algorithm that $L^*(i) \leq L(i)$. Hence, this heuristic function, $L^*(i)$, and the condition guarantee that optimal nodes are selected for the path.

To discuss how the algorithm works, consider the traditional search by human judgement beginning at node P11 and the nodes that can be added to the path using Eq. (1). Possible nodes are P12 and P21. To move from P11 to P12, the cost would be K(P12) = 2400 (the unit of THB is hereafter neglected for convenience). Also, L(P12) is the cost to move from P12 to the next node on the path toward the goal of P33, where the next node could be P13 or P22. If one chooses the path via P22, there are three possible paths, which arrive at P32, P23, and P33. It is clear that $L(i)$ must be known at every node. This implies that the algorithm requires a recursive process to find the correct value of $L(i)$. This eventually leads to all the nodes being visited.

However, under A* using Eq. (2), $L^*(i)$ can be estimated to obtain the best node to move to. It is easy to see that L^*(P22) = 4400, L^*(P21) = 7400, and L^*(P12) = 9000. Comparing the three possibilities, one obtains

$$J^*(\mathrm{P12}) = K^*(\mathrm{P12}) + L^*(\mathrm{P12}) = 2400 + 9000 = 11400, \tag{3}$$

$$J^*(\mathrm{P21}) = K^*(\mathrm{P21}) + L^*(\mathrm{P21}) = 3500 + 7400 = 10900, \tag{4}$$

$$J^*(\mathrm{P22}) = K^*(\mathrm{P22}) + L^*(\mathrm{P22}) = 2500 + 4400 = 6900. \tag{5}$$

It is now clear that P22 is the best choice among the three possible search paths. This is how the A* algorithm can be used to eliminate visiting nodes. Hence, the condition of selecting the lowest cost is satisfied to guarantee the lowest cost for re/upskilling courses. This implies that the algorithm can be used to transform traditional task-based training into a self-directed learning culture.

Table 2
Training cost per head in THB for each Cn.

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
THB	2400	2600	3500	2500	4600	3000	3100	2700	5000	2800	4500	2400	6800	5200	2700	2000

5. Conclusion

In this paper, an optimal path planner for recommending training for new S-curve reskilling/upskilling with the minimum cost is presented. The A* algorithm is applied to a graph created from a regular grid of costs of possible training opportunities, where the resulting graph is highly connected. The result of our simulation shows the effectiveness of the algorithm, indicating that the A* path planner can be used with zone-based training programs for CDAP users and can be transformed into a graph. A limitation of the A* algorithm is that it is difficult and complicated to use as a path planner when factors additional to budgeting factors must be considered when generating a path. In such a case, Bellman–Ford-like algorithms may be better, which would be suitable for investigation in further research.

Acknowledgments

This research was supported by National Research Council of Thailand under the fiscal year 2021–2022. We would like to thank Dr. Pongthip Arunwatthanaporn and his team at Integra8T Company Limited for supporting the data collection and helping develop the platform.

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