Chapter 7

Flexible Research alleyway creation using ACO

7. Ant Quest Algorithm for Flexible Research Alleyway creation with Ant Colony Optimization
With the production of the procedure of Internet technologies, various Trainee-basic
e-ability gateways have been started. To provide for implementation matures’ requires,
the idea of “Research on Demand”, defined by the process of using technology to
enable and encourage workers, managers, and executives to learn and acquire new skills
while resolving organization’s problems, has emerged. An advanced e-ability gateway
should offer such resilience for the Trainees position on their ability goals. We suggest
Effective Research Direction Instructor, a set of course sequencing algorithms that combine
both authoritative navigation rules and inductive methods. Our analysis attempt center of
attention on the final, where we suggest a methods i.e stimulated by a particular technique
in an promoter-point yielding enumerate technology field called “nature-categorize
promoters”.

Nature-categorize promoters are in different structures similar to Ant Colony
Development, Particle Swarm Development, wasp task differentiations, and so on. An Ant
Colony Development methods have been developed for efficient research direction
instructor. The authoritative regulations projected by designer analyst, design the
balancing element to the stimulation methods. The ability of direction find ant quest
algorithm process initiates beginning deal with a novel route. At the recent phase, with no
considerable quantity of trainee history, effective research direction instructor suggests
ability of the route position on the authoritative rules. However, effective research direction
instructor would not create the advice an authoritarian instructions and in its place permit
the Trainee to discover an another route at her own will. The Trainee’s achievement in
ability beginning everything will be calculated and accumulated. The Trainees’ achievement
records are therefore progressively manufactured. By fulfilling confident circumstance, the
training methods are produced. While the subsequently new Trainee records on the scheme
cxiii
will choose up to definite number of earlier alumni who have related summaries. The routes they have in use and their behavior are evaluated by the nature-categorize promoters technique to make a route for the new Trainee. On the other hand, the authoritative route is not completely thrown away. In its place it is managed as a “essential Trainee’s” selection of a route that brings confident weight in the calculation. Therefore, the grouping of regulation-position direction and stochastic calculation in route choice is accomplished. We consider that our access is one of the primary path arrangement methods that clearly merge reliable and inductive planning.

7.1 Composition analysis with Flexible Research using Ant Quest Algorithm

To make easy ability on the requirement in the circumstance of an e-ability gateway, thoughts in our mind is the usual Intelligent Tutoring System's regulation-position route arrangement methods, set of course development methods wherever an ability route, i.e. a sequence of prearranged ability entities, is preference given by an ability. One fundamental fault of the designer, even though its potential of developing ability route adapted to respective existing knowledge position, is that the direction-finding is position on a only rule: find out precondition knowledge initial. The learning guide get better upon that by adding up more metadata categories to allow substitute route choice to matching Trainees with different ability styles. a number of differences of such methods in e-ability situations are recorded in additional modern research system, in peculiar, shifts elsewhere beginning preceding regulation-position development and in its place allocated loads to particular links according to how suitable individual routes are for a particular Trainee with respect to her profile, and subsequently makes use of the weights to recommend the next ability object
upon the Trainee’s completion of the current one. However, authoritative rules are typically designed position on commonsense or expert notions of how a ability route should be chosen, which are not always valid and could be relatively rigid. Brookfield suggests an alternative approach, “successful self-directed Trainees place their ability within a social setting in which the advice, information, and skill modeling provided by other Trainees are crucial conditions for successful ability. The dispute discovers repetitions in the in order navigation research, wherever the phrase community direction-finding has been invented to depict study echo’s the truth that direction-finding is a community and regularly a shared process. In distinct, circuitous community direction-finding develops map outs of communications left by others and can be used as the source of a proposal system. In the light of the alternative notion, Internet-position e-ability technology facilitates convenient collection and analysis of the activity logs, the performances and the results of a large pool of Trainees. That opens the door for analyst to look into data mining-like, constructive induction methods where the historical data of previous Trainees’ ability routes or actual performances can serve as a basis in selecting ability routes for new Trainees. For example, the Web “tour guide” promoter Web Watcher.

Accompanies thousands of users from page to page as they browse the web, and generate a “route”, which is an ordered set of web pages, for each particular topic that maximizes the amount of relevant information encountered. Similarly, the Tutor promoters to develop a statistical model of student behaviors position on past students’ choices of ability routes. Such promoters recommend the next ability media type to a new student after she finishes her activity under the current media type. The e-ability gateway Knowledge Sea efforts in the similar approach as Web viewer except for that a Time used up analysis algorithm was recycled. Huang, Chen & Cheng recommended an enhanced access that
creates make use of Frequent Pattern tree technique to create several stages of conceptual proposals in its place of particular stage regular model taking out results as its ancestors do.

Our proposed effective research direction instructor algorithm is one of the earliest applications of the nature-categorize promoters techniques in course sequencing that make use of past Trainees’ performances as the basis for route recommendations. After an extensive literature search for related work, we only managed to identify four such systems.

7.2 Ant Colony Development and its Applications for Flexible Research using Ant Quest Algorithm

In the usual phenomenon of “Ant Colony Development”, ants build networks of routes that join their nests with accessible food resources. These networks design minimum spanning trees, reducing the energy ants use up in bringing food into the nest. This worldwide best possible structure come outs from the easy actions of the respective ants. Steels proposes a model where all ants share the same set of five rules to govern their actions: Avoid obstacles.

- amble at random, in all-purpose direction of any close to pheromones
- If the ant is holding food, drip food pheromone even as watching for and subsequent a encouragement that guides in the broad route of nest. If the ant is not holding food, drip nest pheromone even as watching for and subsequent a food pheromone track.
- If the ant discovers itself at food and is not holding any, select the food up.
- If the ant discovers itself at the nest and is transportation food, drip the food.

Because only food-carrying ants drop food pheromone, all food pheromone routes
lead to a food source. Once a full ant finds its way home, there will be nest pheromone routes that lead. The initial route will not be straight, but the tendency of ants to wander even in the presence of pheromones will generate shortcuts across initial meanders.

The ant route planning methods has inspired algorithms[]for planning routes in the Travelling Salesman Problem that is to find a tour of minimal length connecting “m” cities; each city must be visited once and only once. In the case where the number of cities is huge, soft computing techniques like genetic algorithms or ant colony development become better alternatives than conventional AI search techniques in Solving such a NP-hard problem. In an algorithm proposed by Dorigo, for example, a huge set of ant-like promoters are moving on the problem graph until each of them completes a tour. Initially, each promoter selects the next connected city randomly when it reaches one city and maintains a memory of the cities it has visited and the distance of each edge. After completing a tour, it lays a quantity of pheromone $P/Q$ on each edge that it has used, where $P$ is a parameter and $Q$ the total length of the tour. With the pheromone being accumulated, each of the subsequent promoters’ selection of the next city to visit when it reaches one city will be influenced by the pheromone of each corresponding edge. There is a probability factor here the greater the value of a particular edge’s pheromone, the higher the probability the promoter selects the edge. This is the key methods to “balance exploitation and exploration” of alternative solutions, the essence of nature-categorize promoters, rather than exploiting the presently known best solution all the way. The technique might not execute strong without pheromone decompose, or it would guide to the strengthening of the primary random variations, which extremely maybe would not be best possible. For that reason, the amount of pheromone that was accumulated previous should be decomposed as time goes by. A number of differences of Travelling Salesman Problem ant colony development
Algorithms have also been practiced to a related problem – communications network routing. Such algorithms propose enhanced results than predictable AI search techniques in behavior dynamic network conditions.

7.3 Research ways from Ant Colony Development with Ant Quest Algorithm

As described before, “conventional” ability route planning can be viewed as finding a route in a course network that leads to one or more ability goal(s), which is analogous to the destination node in network routing. As our research objective is to derive a stochastic methods that involves the alumni’s selection of routes and actual performances, the ant colony development metaphor has offered a plausible and perhaps powerful solution the pheromones. In adapting ant colony development for effective research direction instructor, we consider a few issues:

7.3.1 Occupying the route network.

while ant colony development Algorithms produce simulated promoters to wander about the network and measure the cost on each edge, effective research direction instructor intends to “induce” good ability route from actual alumni’s performance. Therefore, in effective research direction instructor, each of the selected alumni is treated as an ant-like promoter that moves on the course network and deposit pheromone along her way.

7.3.2 Comparison of the ant-like promoters.

The ant colony development Algorithms for all time occupying all search space with uniform promoters. With this involvement in mind, efficient research direction instructor requires alumni that are comparable to the current Trainee to occupying the route network so that the proposal could modify to individual Trainees’ requires or preferences. on the other hand, since Trainees with varied preferences could be enrolled in the same route, effective research direction instructor has to reselect guidance cases and recomputed the...
pheromones each time a new Trainee is enrolled.

7.3.3 Where the pheromones are generated.

In many ant colony development position applications like network routing, each node is only a point where promoters drop by while the real performance measurement is the time spent on each edge. In a course network, however, a Trainee actually spends her time when attempting the nodes while an arc merely reflects the relationship between two nodes. Moreover, a Trainee’s performance at a node is often influenced by the combination and the sequence of the nodes she had visited prior to that. Therefore, the pheromone generated at a node should reflect the “goodness” of the previous arc. For example, if a Trainee visits node “b” right after node “a”, the pheromone generated at node “b” should be attributed to arc (a,b) instead of any “outbound” arc of node b. However, at which node a pheromone value should be stored could become tricky when the system needs to make use of it for recommendations. We will address this issue in a later section.

- Whether the time-decaying feature of the pheromones should be incorporated into effective research direction instructor. The reasons such a feature is incorporated in the original ant colony development Algorithms are (i) To let the earlier promoters’ findings gradually evaporate; (ii) To cope with the dynamic environment in certain applications.
- Reason (i) is relevant to effective research direction instructor in an indirect sense that when a greater set of historical data is accumulated, the number of Trainees that are more “similar” to the current Trainee tends to increase, resulting in more “accurate” pheromones/recommendations. Reason (ii) is also valid in effective research direction instructor because of the possible updates of the course content such as addition or deletion of ability nodes, and amendment of the contents in the existing ability...
nodes which is not unusual for e-ability gateways in the 21st century. Such updates might affect the overall performances of “similar” Trainees who are enrolled in the course at different periods of time, making the previously deposited pheromones less accurate in predicting the performances of new Trainees. Two important assumptions of effective research direction instructor are:

- There are a lot of Trainees enrolled in an e-course or a set of overlapping e-courses at different periods of time to guarantee sufficient “training data”; and
- Many Trainees are adventurous enough not to always follow system recommendations - otherwise, effective research direction instructor will keep on “exploiting” the authoritative route instead of “exploring” alternative routes. For assumption (2), the “rebellious mindset” is more likely to be found in adult Trainees than young students, especially if those who are attempting Ability on Demand are time pressed to accomplish their ability goals. Therefore, we predict that effective research direction instructor would work better for adult ability.

7.4 Initiate portraits in a effective research direction instructor Established System using Ant Quest Algorithm

A Trainee profile, the key resource for facilitating the process, consists of two components: (1) Trainee attributes; (2) activity log. “Trainee attribute” is a way of quantifying a Trainee's relevant background, prior knowledge, ability preferences, and other Trainee information. The system needs it to compute the similarity levels between individual alumni and the current Trainee whom the system recommends a new ability route to. We refer to the latter as “target Trainee”. There are two ways to obtain such information: (1) each Trainee fills up a pre-enrolment questionnaire and/or go through a pre-assessment (for both the alumni and the new
Trainee); (2) the system to analyze a Trainee’s activity log and performances after she has finished the course (for the alumni only). The Trainee attributes and their grading schemes are:

- Prior knowledge and skill set (as specified by e-course designer): Each Trainee grades her competency on individual knowledge/skill in the scale of 1 (never learnt) to 5 (excellent), and/or go through a pre-assessment (the results will be normalized and rounded up to an integer between 1 and 5);

- Ability Preference I – Concept-Task spectrum: Each Trainee grades her preference, emphasis and competency in ability conceptual or practical knowledge (1 to 5);

- Ability Preference II – Specialization-Generalization: Each Trainee specifies whether she prefers to learn specialized before generalized knowledge (1), or vice versa (5);

- Ability Preference III – Abstract-Concrete: Each Trainee specifies whether she prefers to learn concrete before abstract knowledge (1), or vice versa (5);

- Ability Preference IV – Free-Guided navigation: Each Trainee grades her willingness to comply to the system’s recommendations of the subsequent nodes to visit, or to explore the course network at her own will, in the scale of 1 (guided navigation) to 5 (free navigation), with 3 as no preference or “not sure”;

- Analytical skill competency: Each Trainee grades her ability in understanding diagrams, flowcharts, etc., in the scale of 1 (poor) to 5 (excellent);

- Language proficiency: Each Trainee grades her proficiency of the language medium used in the e-course, in the scale of 1 (very poor) to 5 (excellent);

- Similarity of occupations: Since a Trainee’s occupation might affect her expectation in what knowledge or skill to pick up in the course, and her ability styles, we will work out a semantic diagram that incorporates popular occupations and provides the similarity grade (1 to 5) between each pair of occupation.
The Trainee attribute set can be expanded to include more factors, e.g., other types of ability preferences, Trainee’s educational qualifications, etc. On the other hand, the Trainee's activity log records the ability route that she has visited and the assessment results. To facilitate effective research direction instructor pheromone computation, the Trainee's assessment results must be stored in node-by-node basis – see Table 1 for an example: Table 1: An example of Trainee’s activity log

<table>
<thead>
<tr>
<th>N</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>r</td>
<td>7</td>
</tr>
<tr>
<td>t</td>
<td>9</td>
</tr>
<tr>
<td>v</td>
<td>6</td>
</tr>
<tr>
<td>s</td>
<td>5</td>
</tr>
<tr>
<td>x</td>
<td>6</td>
</tr>
</tbody>
</table>

The example shows that the ability route is r (7) → t (9) → v (6) → s (5) → x (6).

7.5 Analysis of the effective research direction instructor Process using Ant Quest Algorithm

The effective research direction instructor ability route development process is an ongoing process. The entire methods can be summarized as the following:

- Recommend a ability route to a new target Trainee at the recent phase of a new course: The human course administrator specifies a “effective research direction instructor training size” m and a “effective research direction instructor training threshold” k.
- Without substantial amount of Trainee history, effective research direction instructor recommends but does not reinforce ability routes position on authoritative rules
  - Past Trainees' (“alumni”) routes and performances are measured and stored
  - Recommend a ability route to a new target Trainee when the number of alumni > 2m: Phase I: Pheromone computation (before the target Trainee starts to study the...
course)

- Computes the similarity levels between individual alumni and the target Trainee
- Choose capable of \((m-I)\) alumni whose comparison levels are superior than \(k\)
- Generates ant-like promoters corresponding to individual selected alumni to traverse the course network and deposit pheromones according to the alumni's performances
- Generates an extra ant-like authoritative promoter to traverse the course network according to the ability route way recommended by the authoritative rules Phase II: Recommend the next node (after the target Trainee starts to study the course)

- Each time when the target Trainee completes studying one node, the system selects and recommends the next node from all the next possible nodes; the higher the pheromones associated to a “next node”, the higher probability that the node will be selected.

- The detailed effective research direction instructor recommendation process is elaborated as below.
Step 1. Start
Step 2. If (Num of alumni > 2m)
   2.1 get current Trainee “t” attribute
   2.2 get next alumnus attributes
   2.3 compute similarity S(t, r)
Step 3. else
   3.1 exit
step 4. if (S(t, r) > k)
   4.1 admit alumni A = A + 1 (Num of admitted alumnus)
   4.2 if (any more unevaluated alumnus)
       4.2.1 goto stop 2(b)
step 5. else goto step 4.2
step 6. if (Admit alumni >= m)
   6.1 rank admitted alumni
   6.2 select top (m - 1) alumni
step 7. else
   7.1 select all Admitted alumni
step 8. exit.

Algorithm 1: effective research direction instructor recommendation process

7.5.1 the Recent Phase of an e-Course

When a new course is launched, there is no Trainee history for effective research direction instructor to compute the pheromones. Therefore, the system can only recommend an ability route position on built-in authoritative rules. In principle, our system only recommends the next node after a Trainee has finished functioning on the current node, albeit disclosing the complete recommended route in one shot is also fine. However, since it is not mandatory for the Trainee to comply with the recommendation, the system may need to re-determine the shortest ability route upon her completion of the next node and to subsequently recommend the following node. So far, the system works in exactly the same way as classic ITS content sequencing techniques. At the same time, Trainees’ ability routes and performances in the course are logged and analyzed. As time goes by, more and more Trainees would have “graduated” from the course. The effective research direction instructor algorithm may then be triggered, depending on the number of the alumni and the effective
research direction instructor training size that the course administrator has preset. For example, if the effective research direction instructor training size \( n = 50 \), the administrator may want to trigger the algorithm when the number of alumni surpasses \( 2n (= 100) \), so that the algorithm would have better chances to identify the subset of alumni who have greater degree of similarity of each new Trainee.

7.5.2 Training by choosing related Alumni

The subsequent to the effective research direction instructor algorithm has been generated, the system will primary choose a set of related alumni to calculate the pheromones. Figure 1 shows the organize diagram of the techniques. The effective research direction instructor's method of identifying similar alumni is inspired by the work by Tang & Chan (2002), which is a quantification technique to cluster a set of students, i.e., homogeneous student group designing for web-position collaborative ability. The technique has been looking into simplifying them to the set of Trainee attributes that will be input to the effective research direction instructor unit for computing the similarity. However, for performance reason, especially that if there are thousands of alumni are available for comparisons, we adopt a simple grading scheme in the scale of 1 to 5 to quantify each Trainee attribute. The Trainee attributes in effective research direction instructor have been elaborated. In essence, effective research direction instructor computes the similarity level \( S(t, r) \) between the target Trainee \( (t) \) and a given alumnus \( (r) \) by the normalized weighted Euclidean distance of their corresponding Trainee attributes.

In the formula, “o” is the quantified value of each Trainee attribute (each type of prior knowledge or skill is treated as one Trainee attribute), and \( w \) is a weight assigned to each Trainee attribute, since there should be different degrees of importance for different Trainee attributes for the comparison. As this is the preliminary version of the effective research
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direction instructor algorithm, we assign *ad-hoc* weights to the Trainee attributes, that is, \( n = 1 \) for each prior knowledge and skill type, and \( n = 3 \) (if the number of the prior knowledge/skill types is \( \leq 5 \)) or \( n = 5 \) (otherwise) for each of the rest of the Trainee attributes. \( N_k(k_t - k_r)^2 \) is where we incorporate the time-decaying feature of pheromones. The time gap between the target Trainee \( (k_t) \) and an alumnus \( (k_r) \) in terms of number of months is/was enrolled in the e-course is squared.

The *ad-hoc* weight of the attribute is 5. Note that the formula itself is a variation of the typical formula of TSP ant colony development, that is, \( S(t,r) = [\sum N_0(o_{t-o_r})^2 + N_k(k_t - k_r)^2]^{-0.5} \) (where \( (k_t-k_r) \) is *inversed* and squared). In our formula, the Euclidean Distance for the time decay is squared (*without* being inversed!) before multiplied by its weight. This is to ensure that both the Euclidean distances of the attributes and time decay have the inversed proportional effects on the degree of the similarity. Next, as the computed values of D is generally high value i.e > 100, by applying inverse and square root to the stated values will produce on Demand very small similarity values i.e < 0.1. Therefore, a smooth extend of the comparison value between 0 (most similar) and 1 (least similar) might be completed. Therefore, instead of TravellingSalesmanProblem ant colony development and communications network router’s ongoing updates of the pheromones in the entire environment throughout the whole course of promoter-position simulations where newly computed pheromone of each edge is added to a fraction of the original value, effective research direction instructor handles time decaying while selecting the “ant-like promoters”.

After that, the alumni will be ranked in the order of individual’s similarity with the target Trainee. Here, we define another parameter – effective research direction instructor training threshold \( k \), which is 0.5 or any smaller value if greater similarity is desired.
serves as a filter for “promoter” selection – alumni whose $S < k$ will not be selected. The top-$(m-1)$ ($m =$ effective research direction instructor training size) alumni whose $S \geq k$ will be selected as promoters.

Step1. start
Step2. create dummy source node
Step3. For each ranked alumnus “i”
Step4. read in all nodes visited
Step5. For each node “a” visited
Step6. read in performance “gw” of next node.
Step7. if (routing table of current node contain required routing record)
   7.1 add “gw” to “AP” of the record in the routing table
Step8. Else
   8.1 create new record.
   8.2 goto step No. 7.1
Step9. If (gw>HIP)
   9.1 HIP=gw
Step10. Else goto step No.11
Step11. If(next node is available)
   11.1 move to next node i.e i=i+1
   11.2 goto step no. 5
Step12. Else if(next alumnus available)
   12.1 get next ranked alumnus i.e r=r+1;
   12.2 goto step no.3
Step13. Else goto step no.3.

Algorithm 2: Algorithm for effective research direction instructor ant route planning

There is still one last “virtual alumnus” who complies with the “authoritative route” and this will be treated as the $(m)^{th}$ promoter. We refer to it as “authoritative promoter”. In the
case where less than m alumni (say, c number of them) satisfy the condition of \( S \geq k \), we will set the weight of the authoritative promoter’s pheromones in the computation as \((m-c)\). In the situation where there are sufficient number of alumni satisfies \( S \geq k \), the system will set \( c = 1 \).

In short, the route way recommendation methods start with having authoritative rules dominating the planning process. As time goes by, the amount of alumni that satisfy the condition may also increase, resulting in gradual decrease of the significance (the weight) of the authoritative rules in effective research direction instructor planning.

7.5.3 Computing the Pheromones

Now that the set of promoters has been identified, effective research direction instructor is ready to compute the pheromones. Algorithm 2a & 2b depict the control diagrams of the pheromone computation process. Since the Trainees are given the resilience to choose whatever next node they want to move to upon the completion of the current node, some “adjacent” pairs of nodes a Trainee has visited may not have “authoritative relationship”, e.g., prerequisite, abstract-concrete, etc., at all. There is no problem for effective research direction instructor to handle such cases by assuming that the entire course network is completely associated, i.e., any given node could association to all extra nodes in rules, and all connections are bidirectional. On the other hand, as stated before, the pheromone stored at a node should reproduce the goodness of the earlier arc in theory. However, when effective research direction instructor makes use of the pheromones to plan the route, a more intuitive way is ant colony development’s representation of “the probability or ‘goodness’ of traveling from current node a to destination node u via the next node b”, which should be stored in a instead of b, even though the pheromone is actually a function of the Trainee’s performance at b. In essence, each node maintains a “local routing table” as shown in Table 2 Routing table of node a to ability goal node u.
<table>
<thead>
<tr>
<th>Via</th>
<th>Collect</th>
<th>Highest entity</th>
</tr>
</thead>
<tbody>
<tr>
<td>J</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>K</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>M</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

The routing table is “local” because it only suggests what the “best” next node is, given the goal node of the course. After the Trainee moves to the next node, it is “none of the (current) node’s business” anymore. On the contrary, conventional routing tables usually store the full route between each source-destination pair of nodes. Prior to the pheromone computation process, the routing table of each node in the course network is blank. Then, effective research direction instructor computes the pheromones position on selected alumni’s history. for instance, an alumnus has selected node “b” later than accomplishing “a”, and her behavior calculation in “b” is “gw” – how to calculate this will be illustrated afterward. So, the system will ensure whether the routing table of node “a” has stored the pheromone of “to u via b”. If so, gw will be combined to the present pheromone value of this exacting record. If not, a new record of “via b” will be formed and hold the primary pheromone value of “gw”. The “uppermost entity pheromone value” (HEP) should accumulate the highest “gw” value between the alumni who have visited “b” via “a”. This field will turn out to be helpful afterward. The process keep on awaiting the complete alumni log has been understand writing in and processed. conversely, given that the primary node an alumnus visited has no “preceding node”, the system will generate a “duplicate source node” as the preliminary point of all the alumni.

After that, the “authoritative promoter’s” route is incorporated into the pheromone computation. Since the route is supposed to be the “best” route in theory, the system “assigns” to the gw value on each node the authoritative promoter has visited by taking the HEP (given the previous node it has visited). However, in case “the authoritative arc (e.g., from node a to node b)” has no pheromone value (i.e., has never been visited by any
alumnus), the system will take the average value of all the HEP values of the other links on the same routing table as the \( gw \) value of the arc.

Finally, each \( gw \) value of the authoritative promoter is multiplied by the weight of the authoritative promoter and then added to the CP on the corresponding routing table (or the system will create a new record if necessary). The following that the HEP fields on all the routing tables can be rejected to complementary the memory space as they are no lengthy required. The performance capacity might subsist of one or some grouping of, but not limited to, the subsequent components, subjected to them being made available:

1. Conclusions of the evaluations of individual nodes the alumni have appointed;
2. Conclusions of the post-evaluation of the entire course: we require to split the results of individual questions to their corresponding nodes
3. Trainee’ self-assessment at the individual nodes.

Each component is assigned a weight and all the weighted values will be added together to yield \( gw \). An alternative way of computing \( gw \) is to combine together the assessment result, if applicable, of and time spent on the same node by taking \( \text{weight} \times (\text{result} / \text{time spent}) \). There is still a weight component here to reflect different levels of significance of the node.

### 7.5.4 Recommending the Next Node

Algorithm 3 shows the control diagram of how the effective research direction instructor algorithm recommends the next node upon a Trainee’s completion of “ability” one node. The pheromone computation with respect to a target Trainee has to be completed before she accesses the first node; and the pheromones will “follow” her until she finishes or quits the course. However, if she spends months on the course and other Trainees have completed the course along the way, the pheromones can be re-computed in the middle of her enrollment to yield better results because of potentially more “similar” aluni. The new
pheromones will not affect the “validity” of what the Trainee has gone through prior to the re-computation due to the local planning nature of the technique. At the beginning, the effective research direction instructor System checks the routing table of the dummy source node to recommend the actual first node to the new Trainee. The relative pheromone value of each entry in the table will determine the probability of the corresponding arc being chosen.

*Table 3: Routing table of dummy node to ability goal node d:*

<table>
<thead>
<tr>
<th>V</th>
<th>Collect pheromone</th>
</tr>
</thead>
<tbody>
<tr>
<td>J</td>
<td>13.5</td>
</tr>
<tr>
<td>K</td>
<td>5.1</td>
</tr>
<tr>
<td>M</td>
<td>40.3</td>
</tr>
<tr>
<td>N</td>
<td>2.2</td>
</tr>
<tr>
<td>P</td>
<td>7.6</td>
</tr>
</tbody>
</table>

Therefore, the probability of choosing node e is 40.3/(13.5+5.1+40.3+2.2+7.6) ≈ 0.604 or 60.4%. In other words, the effective research direction instructor System constructs a roulette wheel that is weighted by CP values. It then spins the wheel to choose the next node to recommend. The Trainee will decide whether she will comply with the recommendation or make an alternative choice of her own. After she has completed functioning on the next node, the process starts all over again to recommend the following node, until the Trainee reaches the goal node. There are a few potential variations of the process:

- Not everyone the “next nodes” in a routing table may “challenge” for being suggested. Those with CP value that is below a pre-defined threshold or a cutoff point will not be included to the roulette wheel.

- Instead of constructing a roulette wheel, list all the “next node” options, in the order of their CP values, and displays their probability values to the Trainee, and let her decide which node to proceed to or even choose a node which is not in the list.

- After the Trainee has been recommended on the next node to visit, she can request effective research direction instructor to pre-compute and display the complete route to cxxx
the goal node via that particular node by applying the pheromone-position methods. This will provide the Trainee a reference of what she can expect ahead.

7.5.5 ERDI Prototype Development and Testing

We have developed a software prototype of the effective research direction instructor System. It is a web-position software running on Microsoft Windows 2000/XP that is interfaced with a simulated web ability gateway. The core route way planning methods is written in C#. The ASP.NET framework is used to develop the web interface so that the prototype is portable to real e-ability gateways that comply with the framework. The simulated web-ability gateway contains a Microsoft Access database that stores test data sets, i.e., individual alumni’s background and e-ability history. The overall architecture of the prototype is depicted in Figure 4.

Algorithm – 3

Step1. start
Step2. get Trainees current node
Step3. for each node in local routing table
Step4. if(CP>cut off)
   4.1 add to roulette wheel table
Step5. Else goto step no.3
Step6. if(next node is available)
   6.1 move to next node
   6.2 goto step no.3
Step7. else if(random selection (roulette wheel))
   7.1 sort AO of nodes in roulette wheel table
   7.2 compute cumulative probability of nodes
   7.3 generate random number and select corresponding node
   7.4 recommend nodes
Step8. Else
   8.1 list all the next node in the order of CP
   8.2 goto step 7.4
Step9. Exit

Algorithm 3 :Control process of recommending the next nodes

The simulator consists of an inference engine, a controller, an inference engine, a
database and an e-ability Gateway simulator. Driven by the effective research direction instructor algorithm, the inference engine computes pheromones and recommends ability routes. The event-driven controller provides the functionality of data feeding, alumni selection and parameters control (training size, threshold values, etc.). The course data and the Trainee performance data are fed into the database which will be retrieved by the inference engine for further computations. The controller also acts as a communication hub among the other modules.

Figure 6: Control diagram of the process of recommending the next nodes

7.5.6 ERDI Instructor simulator

The e-ability gateway simulator was designed with the purpose of simulating the integration between the e-ability system and the effective research direction instructor. The simulator only feeds the test data into the inference engine, collects new Trainees’ preferences and displays the recommended ability route way or the next ability node. The test data consists of the course structure and alumni’s performance records. It accepts the user input and would be redirected to effective research direction instructor for recommending the
best route way. Currently, we have validated and verified the prototype with simulated data. There are two different categories of test cases: (a) where number of “similar” (to the target Trainee) alumni << preset effective research direction instructor training size; (b) where number of “similar” alumni > effective research direction instructor training size. As an illustration, consider the following test cases that are subjected to the authoritative and inductive route ways below,

- **Authoritative Route way** – ability object IDs (nodes):
  \[1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 8 \rightarrow 9 \rightarrow 10 \rightarrow 11 \rightarrow 12\]

- **Inductive Route way**:  \[1 \rightarrow 2 \rightarrow 5 \rightarrow 6 \rightarrow 12\]

- **Test Case X (where number of “similar” alumni << training size)**
  - Training Size = 500
  - Training threshold = 0.4
  - Test Set = 300 “similar” alumni + 200 “random” alumni
  - Eventual recommended route way : \[1 \rightarrow 2 \rightarrow 3 \rightarrow 4\]

- When the effective research direction instructor unit is activated, 303 alumni records were selected while the authoritative promoter carries a weight of \[500-303=197\]. We would expect that the eventual recommended route way is the same or similar to the authoritative route due to the relatively heavy weight of the latter. Instead, the recommended route way is terminated at node 4 because very few alumni have visited node 4 position on the simulated Trainee history. In reallife, when there is enough training size, such a “broken link” problem is very unlikely to occur. However, as it is a potential issue to effective research direction instructor, we modified the algorithm by allowing the “routing” to proceed to the next node with much lower AP value as long as the student has yet to reach its ability goal. After the modification, the recommended route way becomes: \[1 \rightarrow 2 \rightarrow 3 \rightarrow \ldots\]
5 → 6 → 7 → 9 → 10 → 11 → 12

- where nodes 4 and 8 are skipped due to low visit rates, according to the simulated data. The new recommended route shows the predominant influence of the authoritative route while the alumni’s historical data still play a small part in varying it.

- Test Case Y (where number of “similar” alumni > training size)

- Training Size = 00

- Training threshold = 0.02

- Test Set = 300 “similar” alumni + 200 “random” alumni

- Genuine advised route way: 1 → 2 → 5 → 6 → 12 → 14

In this case, with enough test set, the result can be expected exactly as all the chosen alumni are having the same background as the user. The random set does not cause obvious effect to the generated route way because the Alumni Selector will select only the top 300. Therefore, the actual recommended route way is identical to the “inductive route way” that we preset for the simulator to generate test data. However, there is still 10% of test set which went through the course network in a random manner. Some simulated alumni have visited some other nodes and yielded “good” results. That explains why node 14 comes into the picture. In summary, in type (a) cases, the effective research direction instructor algorithm tends to recommend route ways that tally with the authoritative route ways as the pheromones deposited by the authoritative promoter carries a greater weight. The greater the number of “similar” alumni increases, the more the recommended route ways reflect the aggregate choices and performance of the alumni. More details of the validation and verification are reported in Lai, Lee, Chong & Ong.