THE STUDY OF USING SELF-LEARNING NEURAL NETWORK IN AUTOMATIC CONSTRUCTION-SITE LAYOUT

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Abstract: A good construction-site layout plan could directly or indirectly save construction cost and improve on construction efficiency; the larger of construction project or higher of construction overlapping is, the more important of construction-site layout is plan. Moreover, today's constructive automatic technique reaches a specific degree; the application of automatic technique in construction-site layout plan has been accentuated. In general, the requirements of construction-site facilities depend on the size and type of construction project. However, a traditional view for arranging construction-site facilities by heuristic mostly causes a disappointing layout plan and makes uncompleted judgement. In this paper, it would formulate construction-site layout problem to combinatorial optimization one. Because it's problematic model of mathematics is NP-complete problem, it would try to adopt self-learning neural network to solve construction-site layout problem. In order to test it's reliability; it will compare quality-efficiency with Random-searching and Annealing Neural Network method.

Keywords: Construction-Site Layout Plan, Scientific Management, Artificial Neural Network, Self-Learning Neural Network

1. INTRODUCTION

Construction-site layout plan is an important construction planning activity. A good construction-site layout plan could directly or indirectly save construction index__and shorten construction period; especially the construction project is large. The requirements for temporal facilities in construction site varies on the scale of construction project and type, for example material stack site, steel bar processing plant, wooden processing plant, agitator car parking site, job office, labor residence, electricity equipment and water supply shop, warehouse, and etc.

Until now, there is no guaranteed way to get the optimal construction-site layout plan. The traditional planning layout emphasizes on the matters that site-people should pay attention to and take into consideration during the procedure of construction-site layout[1,2]. Based on the researches, the materials stacking by labor or heuristic is mostly widely used[3]. However, it easily causes unreasonable deployment and increases unnecessary moving cost. Because of scientific management's emergence, it provides an efficient way to solve the problem through quantitative technique. In 1973, Warszaski[4] initially established factor-quantity technique for materials transportation-time; Gates and Scarpa[5] offered the optimal moving model for materials transportation-time in 1978; Tommelein[6] applied quantity data in MovePlan that is a interactive software to design materials moving planning in 1991; Chang, L. C.[7] used MRP to plan factory deployment in 1988; Lee[8] took steel bar deployment as an example to evaluate and prove the numbers of materials layout sites would affect the transportation cost in 1997; Hamiani[9] applied construction-site layout plan of temporal facilities in expert system in 1989; layout problems that mentioned above are evaluated the reliability of the solutions by exchanging between facilities.

However, in 1995, Yeh [10] found that evaluating layout case by inter-exchange facilities would not suitable while formulating construction-site layout problem to the combinatorial optimization problem. Because of its problematic combining-explosion, it is appropriate to adopt Annealing Neural Network to solve the problem. It is found that the effects of parameter-definition and initiated-solution of this method causes conflicts between network-absorption and solution-quality during the procedure of testing. The bigger scope of the problem is, the more obvious impact is. This is why searching a new algorithm technique is so important. In order to decrease the scope of research, this paper would limit construction-site facilities problem is to design the optimal layout for a specific objective while limiting a set of pre-determined temporal construction facilities in a set of pre-determined sites. It is advised that using a method, self-learning neural network that proposed by Yang[11] in 1997, to solve this problem because there is no disadvantage of parameter-definition like ANN and it could efficiently get a high-quality solution.

In this paper, I will divide into 5 parts. Firstly, I will give an introduction for this paper. Secondly, it is designed to establish a problematical math model. Thirdly, there is an application of self-learning neural network. Fourthly, I will take an example to clarify tested results and parameter-defined. Finally, I will give a conclusion and summary.

2. THE ESTABLISHMENT OF PROBLEMATIC MATH MODEL

The assumptions for construction-site layout problem are as follows:

1. there are n temporal construction-site facilities problem and coincidentally n pre-determined sites are available;
2. each temporal construction-facility need a site only to place;
3. each site can only be placed for one construction-facility;
4. any temporal construction facility could place in any site;
5. any site could be placed for any construction-facility.

From the problematic assumptions that mentioned above, it is found that the problem limits the relationship between construction facility and site is one to one; moreover, the objective of problem is to search the lowest construction-site layout index. The mathematics model formulation for construction-site layout problem is given as follows:

$$Min\ Z=\sum_{x=1}^{n}\sum_{i=1}^{n} X_{xi}C_{xi} + \sum_{x=1}^{n}\sum_{i=1}^{n}\sum_{y=1}^{n}\sum_{j=1}^{n} X_{xi}X_{yj}A_{ij}D_{xy} \qquad (1)$$

s. t.

$$\sum_{j=1}^{n} X_{xj} = 1\ ,\ x=1\sim n \qquad (2)$$

$$\sum_{y=1}^{n} X_{yi} = 1\ ,\ i=1\sim n \qquad (3)$$

$$X_{xi} \in \{0,1\} \qquad (4)$$

Z: objective function. Searching for the lowest layout index of construction-site facilities.

C_{xi}: index matrix of construction-site facilities. It means layout index of temporal facility x is assigned to a site i; if C_{xi} becomes smaller, it represents that temporal facility is more appropriate to place in this site.

A_{ij}: related matrix of site. It means that if site i is next to j, then $A_{ij}=1$; else $A_{ij}=0$. The bigger of A_{ij} is, the stronger of relationship of two sites is.

D_{xy}: inter-active index matrix of facility. It represents the index of facility x is next to y; the bigger of D_{xy} is, the higher inter-active index of temporal facility.

X_{xi}: decisive variable. If $X_{xi}=1$, then temporal facility x is placed in site i; else $X_{xi}=0$. $X_{xi}\in\{0,1\}$.

n: the number of available placed construction-facility sites.

i, j: index of site.

x, y: index of temporal facility.

The decisive variable of problematic math model that mentioned above is represented by binary. There is n^2 problematic decisive factors and constraints are 2n. Because the problem limits the relationship between construction facility and site is one to one, the possibly efficient solutions reach n! (n=12 means legal combinatorial solutions are 12!. If using random-searching method to gradually get all solutions, it may takes a long time. That is why it is advised that using "self-learning neural network" method to solve this problem.

3.THE APPTLICATION OF ARTIFICIAL NEURAL NETWORK

Artificial neural network, a complicated and calculated network by combining massive simple neural components, is a calculated tools that simulating the process of human's thinking. At present, the application of artificial neural network could divided into 4 categories that are Supervised learning network, Unsupervised learning network, Associate learning network and optimization application network. Among these networks, the optimization application network has been widely used in solving the combinatorial optimization problem. Hopfield and Tank are the first one to propose that using artificial neural network to solve the combinatorial optimization problem. They offered a Hopfield-Tank neural network that efficiently solve TSP problem. This is a threshold for using artificial neural network in solving the combinatorial optimization problem.

Ping-Chung Yang proposed Self-Learning Neural Network that is derived from amended YY network algorithm 〔11〕 in 1997. It is a two-step optimal network model and mostly used to solve the optimal limited satisfied problem. Self-Learning neural network is developed by demand into three types: binary, digital and combined type 〔11〕. Because decisive variables of mathematics model are binary (0,1), it is suitable to solve it by 2-type self-learning neural network. Conditioned variables of neural network unit are represented by 2-dimension matrix. Each decisive variable of the matrix represents a neural unit. Each neural unit has conditioned factor and neural quality (if the neural quality is higher than 0, and then neural unit is in exciting situation; otherwise, it is in a restricted situation). The below that mentioned illustrates the characteristic equation establishment of neural network quality movement, procedure of network algorithm and take an example to describe the process of network algorithm.

3.1 The characteristic equation establishment of neural network quality movement

Two requirements needed to satisfy the establishment are as follows:

(1)Objective: search for the lowest layout index for temporal construction-site facility.

(2)Constraints: each temporal facility could only place on one site and each site must be placed.

In order to satisfy the requirement, characteristic quality movement equation of E1(objective), E2(objective), E3(constraint) are established.

Characteristic quality movement equation E1:

$$E1_{xi}=\alpha\cdot(1-C^{*}_{xi}) \qquad (5)$$

α : index parameter($\alpha>0$). Learning process is α_L, recalling process is α_R.

C^{*}_{xi} : normalize to facility index matrix, $C^{*}_{xi}=C_{xi}\,/\,\underset{x,i}{Max}\,C_{xi}$.

Characteristic quality movement equation E2:

$$E2_{xi}=-\beta\cdot\left(\sum_{y=1}^{n}\sum_{j=1}^{n}V_{xi}V_{yi}\,A^{*}_{ij}\,D^{*}_{xy}\right) \qquad (6)$$

β : inter-active parameter($\beta>0$) . Learning process is β_L, recalling process is β_R.

A^{*}_{ij} : normalize to site-related matrix, $A^{*}_{ij}=A_{ij}\,/\,\underset{i,j}{Max}\,A_{ij}$.

D^{*}_{xy} : normalize to inter-active index matrix, $D^{*}_{xy}=D_{xy}\,/\,\underset{x,y}{Max}\,D_{xy}$.

Characteristic quality movement equation E3:

$$E3_{xi}=-\gamma\left[\left(\sum_{y=1}^{n}V_{xj}-1\right)+\left(\sum_{j=1}^{n}V_{yi}-1\right)\right] \qquad (7)$$

γ : limited parameter($\gamma>0$). Learning process is γ_L, and recalling process is γ_R.

The combination of $E1_{xi}$, $E2_{xi}$ and $E3_{xi}$ is the total characteristic quality movement equation. Because it is referred to the characteristics of problem, it is directly apply to network to calculate neural unit.

The description of characteristic quality movement equation is as follows:

1. $E1_{xi}$ means that facility layout index matrix mirrors to equation. Because $C^{*}_{xi}\leq 1$, $E1_{xi}$ is a increasing quality.
2. $E2_{xi}$ means inter-active facility index mirrors to equation.
3. $E3_{xi}$ means that it limits that only one exciting neural unit exists in each line or row of neural unit variables exist. Form the structure of quality; this includes penalty and increasing energy.

3.2 Network algorithm process

step 1.0 : Establish fundamental data

step 1.1 : Set *V*(neuron state variable matrix), *U*(neuron energy matrix)

step 1.2 : Read related matrix *C*, *A* and *D* of problem; normalize these to *C**, *A**, *D**

step 2.0 : Learning process

step 2.1 : Set learning process parameter

Set parameter α_L, β_L, γ_L, T_L(learning iteration number), U_{Lmax}(learning process neuron energy upper bound), U_{Lmin}(learning process neuron energy lower bound), U_{bound}(neuron energy bound)

step 2.2：Calculate neuron energy

define *X, U* are 0 matrix, *t=0*

do until $t=T_L$

$t=t+1$ （$x=1\sim n, i=1\sim n$）

if $U_{xi}(t-1)\neq U_{bound}$ *then* $U_{xi}(t)=U_{xi}(t-1)+E_{xi}$

if $U_{xi}(t)>0$ *then* $V_{xi}(t)=1$ *else* $V_{xi}(t)=0$

if $U_{xi}(t)>U_{Lmax}$ *then* $U_{xi}(t)=U_{Lmax}$

if $U_{xi}(t)<U_{Lmin}$ *then* $U_{xi}(t)=U_{bound}$

loop

step 3.0：Recalling process

step 3.1：Set recalling process parameter

Set parameter α_R, β_R, γ_R, T_R(recalling iteration number), U_{Rmax}(recalling process neuron energy upper bound), U_{Rmin}(recalling process neuron energy lower bound)

step 3.2：Compression neuron energy

if $U_{xi}(t)\neq U_{bound}$ *then* （$x=1\sim n, i=1\sim n$）

if $U_{xi}(t)>0$ *then* $U_{xi}(t)=U_{xi}(t)\cdot(U_{Rmax}/U_{Lmax})$

if $U_{xi}(t)<0$ *then* $U_{xi}(t)=U_{xi}(t)\cdot(U_{Rmin}/U_{Lmin})$

end if

step 3.3：Run recalling process

t=0

do until $t=T_R$

$t=t+1$ （$x=1\sim n, i=1\sim n$）

if $U_{xi}(t-1)\neq U_{bound}$ *then* $U_{xi}(t)=U_{xi}(t-1)+E_{xi}$

if $U_{xi}(t)>0$ *then* $V_{xi}(t)=1$ *else* $V_{xi}(t)=0$

if $U_{xi}(t)>U_{Rmax}$ *then* $U_{xi}(t)=U_{Rmax}$

if $U_{xi}(t)<U_{Rmin}$ *then* $U_{xi}(t)=U_{Rmin}$

It is judged as a legal solution.

Save solving

loop

step 4.0：End. Output optimal solving.

3.3 Description of sample

We take 5 samples of temporal construction-site facility layout to demonstrate the procedure network algorithm.

Firstly, establishing each construction-site facility layout index as table 1; the relationship of facility and facility is as table 2 and 3; transfer these into *A* and *D*; for *A*, a neighboring site index is 1 and otherwise is 0; for *D*, a closer inter-active facility index is -10 and otherwise is 10. It can be given as table 5.

Table 1 Index matrix C of facilities layout

	Site 1	Site 2	Site 3	Site 4	Site 5
Facility 1	3	6	1	8	10
Facility 2	2	4	1	8	9
Facility 3	9	5	7	1	2
Facility 4	2	2	5	1	1
Facility 5	4	8	5	3	9

Table 2 Neighboring relationships between sites

No. of site	No. of neighboring site
1	2,4
2	1
3	5
4	1
5	3

Table 3 Inter-active relationship of facilities

No. of temporal facility	Name of temporal facility	No. of temporal neighboring facility	No. of against temporal facility
1	Site 1	3	---
2	Site 2	---	4
3	Site 3	1	---
4	Site 4	5	2
5	Site 5	4	---

Table 4 Relational Matrixes A of Sites

	Site 1	Site 2	Site 3	Site 4	Site 5
Site 1	0	1	0	1	0
Site 2	1	0	0	0	0
Site 3	0	0	0	0	1
Site 4	1	0	0	0	0
Site 5	0	0	1	0	0

Table 5 Inter-active index matrixes D of facility

	Facility1	Facility 2	Facility 3	Facility 4	Facility 5
Facility1	0	0	10	0	0
Facility 2	0	0	0	-10	0
Facility 3	10	0	0	0	0
Facility 4	0	-10	0	0	10
Facility 5	0	0	0	10	0

Then, it defines *V* and *U* are 0-matrix and normalizes *C*, *A* and *D*. The all indexes of *C* is divided by 10(the largest layout index) to get the sequential values from 0.0~1.0.（for example: the transferred index of facility 1 and site 2 is equal to 6/10=0.6）. Because there are negative values among *D*'s indexes, it is necessary to transfer inter-active index to the sequential values from 1.0~1.0 by using the same way to transfer *A* and *D*.

Learning parameter α_L=1.5, β_L=7.0, γ_L=1.0, T_L=10 times, U_{Lmax}=20.0, U_{Lmin}=-20 and U_{bound}=-100 to defined and energy of neural network unit is calculated (network is sequential executed). The executing phases are doing *x* firstly and then *i* next as follows: while *t*=1, *x*=1, *i*=1：$U_{1,1}(1)=U_{1,1}(0)$ +3.05 =0+3.05=3.05 > 0，it instantly change the situation of neural unit $V_{1,1}(1)$ =1；until finishing all energy calculation of neural units. In this time, the learning iteration time is *t*=1. If $U_{1,1}(1)>U_{Lmax}$ during the calculated process, then $U_{1,1}(1)=U_{Lmax}$. If energy of neural unit $U_{1,1}(1)<U_{Lmin}$, then $U_{1,1}(1)=U_{bound}$. In the continual iteration processes, if $U_{1,1}(1)=U_{bound,}$ then skip energy calculation of this neural unit. If iteration times is $t=T_L$, then end the learning of network. The neural unit's final situation in the final phase of learning is presented in table 6 and energy of neural unit is in table 7.

Table 6 Situated variables matrix of neural unit V (t=10)

	Site 1	Site 2	Site 3	Site 4	Site 5
Facility 1	0	0	1	0	0
Facility 2	1	0	1	0	0
Facility 3	0	0	0	1	0
Facility 4	0	1	0	1	1
Facility 5	0	0	0	0	0

Table 7 Energy matrix of neural matrix U (t=10)

	Site 1	Site 2	Site 3	Site 4	Site 5
Facility 1	-7.50	-8.00	3.50	-7.00	-2.00
Facility 2	20.00	-1.00	13.50	-17.00	-10.50
Facility 3	-6.50	-2.50	-3.50	1.50	-0.00
Facility 4	-5.00	20.00	-10.50	20.00	12.50
Facility 5	-10.00	-5.00	-4.50	-0.50	-0.50

Furthermore, define recalling parameter of network α_R=0.1, β_R=0.1, γ_R=1.0,T_R=50 times, U_{Rmax}=10.0, U_{Rmin}= -10.0 ; processing energy expression of neural units(if energy of neural unit is U_{bound} then skip the energy calculation of equation while executing recalling process equation of energy equation). While the iteration time of network is 8-time, it generates a first legal absorption as table 8 and 9.

Table 8 Conditioned variable matrix of neural unit V (t=8)

	Site 1	Site 2	Site 3	Site 4	Site 5
Facility 1	0	0	1	0	0
Facility 2	1	0	0	0	0
Facility 3	0	0	0	0	1
Facility 4	0	1	0	0	0
Facility 5	0	0	0	1	0

Table 9 Energy matrix of neural unit U (t=8)

	Site 1	Site 2	Site 3	Site 4	Site 5
Facility 1	-1.19	-2.68	1.17	-5.34	0.00
Facility 2	7.04	-6.02	-0.23	-9.94	-8.99
Facility 3	-2.17	-0.85	-2.51	-1.53	1.34
Facility 4	-9.92	1.44	-9.95	-0.68	-2.73
Facility 5	-2.52	-1.34	-1.85	0.31	0.17

While iteration time is $t=T_{R,}$ end the recalling of network. In the final, the combinatorial numbers of solution are 2; the average value of solution is 2.5; the optimal index of layout is -5.0; table 10 represents the solution combination.

Table 10 The combinatorial optimization combined solution of construction facilities (index: -5)

No. of facility	No. of Site	Layout index of facility	Inter-index of facility
1	3	1	0
2	1	2	-10
3	4	1	0
4	2	2	-10
5	5	9	0

4. COMPARISON OF CASE STUDY RESULTS AND NETWORK PARAMETERS DEFINITION

4.1 Case study

In this case, there are two neighboring eight-story buildings that are office and lecturing buildings in a campus. There is a limit of construction site is that deploying temporal construction facility in limited sites. Because there are 12 temporal construction facilities, it is designed 12 temporal sites to layout. The layout of construction site is demonstrated by illustration 1.

Table 11 is an index relationship between facilities. The inter-active index is -50 while the relationship between facilities is neighboring; the inter-active index is 100 while one against to one; in addition, the index of neighboring site is 1.0, the site index is 0.5 if site is next to neighboring site; others are 0.0.

The basic parameter-defined of self-learning neural network is as follows:

α_L= 1.50, α_R= 0.1, β_L= 7.00, β_R= 0.1, γ_L= 1.00, γ_R= 1.00, T_L=24 times, T_R=24 times, U_{Lmax}= 20, U_{Lmin}= -20, U_{Rmax}= 20, U_{Rmin}= -20, U_{bound}=-100 ;

The 28 varied combination of each parameter are as follows: α_L= 0.50, 1.00, 1.50, 2.00, 2.50 ; $\square_R$ = 0.1, 0.20, 0.30 ; $\square_L$= 4.0, 5.0, 6.0, 7.0, 8.0, 9.0 ; $\square_R$= 0.1, 0.20, 0.30 ; T_L= n, 2n, 3n ; T_R= 10n, 20n, 30n ; U_{Lmax}= 20, 30, 40 ; U_{Lmin}= -20, -30, -40 ; U_{Rmax}= 10, 20 ; U_{Rmin}= -10,-20;

The tested results are represented in table 12. The percentage of network absorption is 100% for all 28 combination; the percentage of network absorption is only 40% for 20 solutions due to the influence of initiated solution. It is found the SLNN is better than ANN in solution quality and stability; m[illegible] e[illegible] n[illegible] s[illegible] h[illegible] n[illegible] d to get 1,000, 1[illegible] 100,000 legal solution[illegible] the s[illegible] n-[illegible] nes better according se[illegible] g times bu[illegible] time is longer to decrease eff[illegible]c[illegible]

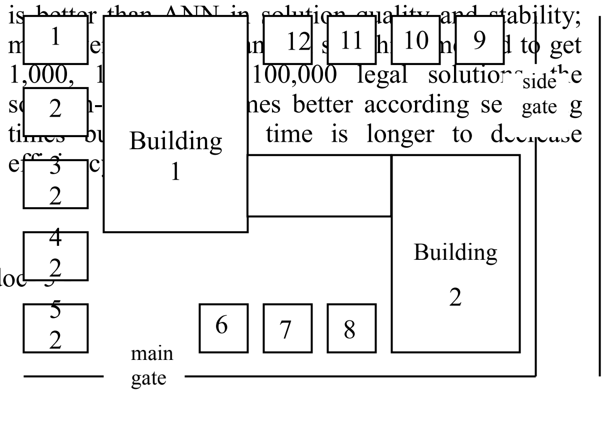

Illustration 1 layout of construction site

Table 11 the index relationship between facilities

No. of facility	Code of facility	Name of temporal facility	No. of neighboring facility	No. of against facility
1	R1	NO.1 of Steel bar processing plant	---	9,10,11
2	R2	NO.2 of Steel bar processing plant	---	9,10,11
3	C1	NO.1 of Wood processing plant	---	---
4	C2	NO.2 of Wood processing plant	---	---
5	F1	NO.1 of Scaffold stack site	---	---
6	F2	NO.2 of Scaffold stack site	---	---
7	B1	NO.1 of Parking space of Agitator car	---	9,10,11
8	B2	NO.2 of Parking space of Agitator car	---	9,10,11
9	JO	Job office	10,11,12	1,2,7,8
10	LR	Labor residence	9	1,2,7,8
11	E&W	Electricity equipment and water supply shop	9	1,2,7,8, 12
12	WH	Warehouse	9	11

Table 12 Tested results and comparison of case

Method Solution	Random Searching (1)	Random Searching (2)	Random Searching (3)	Annealing Neural Network	SLNN
Max.	1,429	1,600	1,597	N.A	26
Average	805	806	799	-131	-135
Min.	-19	-54	-126	-142	-143
Standard Deviation	244	255	253	8.6	N.A
Performing Time	15 seconds	148 seconds	1520 seconds	40 seconds	23 seconds

Note: the tested standard of performing time is using Pentium 166 MHz Processor.

Table13 is the combinatorial optimization solutions. If it is the optimal solution by using this method, the index 107 of facility is close to the optimal value 90. In addition, comparing table 11 and 13, it is found that inter-active requirement of facilities is satisfied and proves that this method efficiently deal the optimal layout problem as illustration 2. From the data that mentioned above, combination of facility-layout index and inter-active index facility by problematic mathematics model to a single objective still exist conflicts between them.

Table 13 The optimal solution for construction-site layout（Total index：-143）

No. of facility	No. of site	Layout index of facility	Inter-index of facility
1	10	6	0
2	12	7	0
3	8	10	0
4	1	13	0
5	7	10	0
6	2	8	0
7	9	7	0
8	11	15	0
9	5	8	-125
10	4	8	-50
11	3	8	-25
12	6	7	-50
Total（index）		107	-250

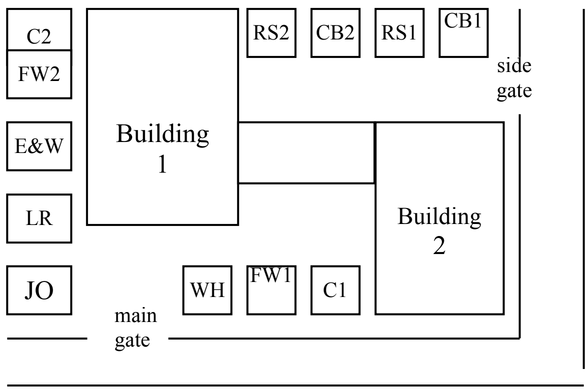

Illustration 2 The optimal solution of construction-site layout（index：-143）

4.2 Definition of network parameters

This section would clarify the influences of parameter's definition to solution-quality.

1. α_L parameter define too high or low is bad to solution-quality; too low would prefer to satisfy constraint to make layout index increasing; too high would prefer to make the deviation between satisfied objective and constraint too large to absorb. It is advised the scope between 1.0~2.0.
2. α_R parameter definition would influence the searching scope of network absorption; too high would make un-absorption; too low would make neural unit inactive to make searching-scope smaller and cannot get the optimal solution. It is advised the scope between 0.1~0.3.
3. β_L parameter define too high or low is bad to solution-quality; too low would make facility-

layout increasing; too high would make inter-index decreasing; It is advised the scope between 0.1~0.3.

4. β_R parameter definition would influence the searching scope of network absorption. It is advised the scope between 0.1~0.3.
5. If iteration time of network learning T_L is too much, the available numbers of executed neural unit would become fewer to absorb; few would make the numbers of available executed neural unit become more. Although increasing the percentage of network absorption, it would decrease the solution-quality. It is advised the scope between $0.5n$~$2n$.
6. The network recalling time T_L is too much, wasted time would decrease time-efficiency. Wasted would decrease time-efficiency; too low to absorb; It is advised the scope between $10n$~$30n$.
7. The definition of U_{Lmax} effects smaller; the definition of U_{Lmin} effects larger; the definition of U_{Lmin} is too high to absorb.
8. The definition of U_{Rmax}, U_{Rmin} of neural unit's energy would influence solution; too large or small to absorb.

5. CONCLUSION

1. It would formulate construction-site layout problem to the combinatorial optimization problem. It would prove that using scientific management method to solve the problem of this field if it would efficiently establish the related requirements between facilities. How to define quality-index is an important considerable factor.
2. Comparing to Annealing Neural network and self-learning neural network, random searching is inferior to these in solution-quality.
3. Because the conflict of parameter's definition and the influence of initiate, the result and efficiency by using Annealing Neural network is inferior to this method.
4. In this paper, it does not take the effect of sizes of construction facilities and sites into consideration. It could be discussed in the future according the requirements.
5. This combined layout index and inter-active cost of facility to a single objective, it may lead to prefer to an objective due to the non-average definition of index. In the future, it may separate it and concerns multi-objective layout problem of construction-site.

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