Artificial Neural Network Based Decision Model for Alternative Workplaces

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Abstract

Alternative workplace arrangements (AWAs), enabled by information and communication technology, where employees do not have permanently assigned workspaces on company premises, are likely to continue in the future. However, facility managers have limited tools to select from among the possible choices in which the AWA type is more appropriate considering their organizations' business reasons for adoption and the current readiness condition. The aim of this research is to provide facility managers with an understanding of the decision process for AWA adoption and to develop a decision support model to allow them to select an appropriate AWA type and determine the anticipated satisfaction level. Using the artificial neural network (ANN) method and the case-based reasoning (CBR) technique, the authors have developed and validated a decision model to suggest the most appropriate AWA type given the organization's objectives and the current readiness levels. The proposed approach is tested by evaluating 64 real adoption cases from 19 large high-tech companies. The findings reveal that the ANN-based decision model can provide an accurate prediction of the actual values and the support decisions of the facility managers responsible for developing workplace strategies to meet the organization's current and future needs.

Keywords: Alternative Workplace Arrangement (AWA); Readiness Level Assessment Indicator (RLAI); Artificial Neural Network (ANN); Case-Based Reasoning (CBR); Facility Management (FM)

1. Introduction

Globalization and advances in information and communication technology (ICT) have led to a revolution as to where, when, and how work is accomplished (Kawai & Shiozaki, 2005). An alternative workplace arrangement (AWA) is a workplace arrangement aided by ICT in which workers can choose to work from a satellite office, telework center, home office, virtual office, or any flexible location outside the traditional central office (Belanger & Collins, 1998; Ndubisi & Kahraman, 2005; Kim & Juan, 2011).

According to Telework Trendlines 2009, more people than ever before were involved in AWA in 2008. This report indicates an increase in the number of people who work from home or from workplaces other than the central office, including satellite and virtual offices, at least one day per month from 28.7 million in 2006 to 33.7 million in 2008 (Johnson, 2009). It is highly probable that the future workplace will be more geographically and virtually distributed and the traditional ratio of workers to workspace will be reduced because of the high real estate cost in urban areas, air pollution, and traffic congestion resulting from mass commuting, as well as the retention strategies for talented workers (Fritz et al., 1996; Roper & Kim, 2007).

Facility management (FM) has emerged and evolved over the past few decades to better prepare organizations for rapid changes in business, influences of ICT, and the dramatic shifts in the requirements for workers focused on knowledge rather than production (Anjum et al., 2004). Today, facilities are beginning to be recognized as strategic business resources, and facility managers are becoming recognized as asset managers commonly responsible for supporting the entire organization (Kim et al., 2008; Qu et al., 2010).

Facility managers have the potential to promote and enhance the AWA environment and are responsible not only for the physical facilities of the central office but also for AWA. However, currently, facility managers are not familiar with the decision-making process and have no established tools to select the most appropriate AWA type considering their organizations' situation. The responsibilities of facility managers extend beyond operational issues to the more fundamental goals of providing high performing and sustainable workplaces (Kaczmarczyk & Murtough, 2002). Most organizations...
face uncertainties while adopting any type of alternative workplace, and the facility manager is the one who plays the important role of a change-master to effectively deal with such changes (Saji et al., 2006). The adoption of an AWA will force some changes in the way organizations adapt themselves to new workplace environments. As the adoption goes forward, the right person to handle the upcoming changes and needs for the AWA adoption is the facility manager, who almost always has a solid understanding of the work, workplace, and people within the organization. Further, he/she regularly measures both the effectiveness and the efficiency of the organization (Ha et al., 2002). Facility managers are responsible for developing workplace strategies to meet the organizations’ current and future needs (McGregor, 2000).

Therefore, the purpose of this research is to develop an AWA decision support model based on the artificial neural network (ANN) method that allows facility managers to select an appropriate AWA type and determine the anticipated satisfaction level. The proposed approach is tested by evaluating 64 real adoption cases from large high-tech companies. The system validation process and the results of the ANN prediction are distinctly discussed in this paper.

2. Review of Alternative Workplace Arrangements (AWAs)

Many researchers use the term AWAs loosely and interchangeably with other terms. However, AWAs, flexible workplace arrangements (FWAs), distributed workplace arrangements (DWAs), remote workplace arrangements (RWAs), telecommuting arrangements, and teleworking arrangements are all similar terms that imply the arrangements of a decentralized organizational structure where the core organization distributes a portion of its functions to a remote site (Venkatesh & Vitalari, 1992; Zhang et al., 2011).

The emergence of AWAs has altered the workplace and work time by changing how work is performed on a regular basis. Responding to the needs of a rapidly changing business environment, companies have created and adopted many different forms of alternative workplaces (Gilbreath & Rees, 1998).

In this research, AWAs are limited to six recurring types divided into two categories (Kim & Juan, 2011): on-site workplaces, such as hoteling, group addresses, and shared offices; and off-site workplaces, such as satellite offices, home offices, and virtual offices. Off-site workplaces are selected on the basis of the place of work. In contrast, on-site workplaces can be differently classified by their space configuration (for example, group office) and usage (for example, hoteling and shared office). Note that only primary places of work and full-time AWAs are considered in this research. Other types of AWAs, such as mixed, part-time, and supplemental work-at-home AWAs are not examined in this research.

| RLAI Category | Variables | Explanatory variables | Definition |
|---------------|-----------|-----------------------|------------|
| Objectives    | X1        | Retention/atraction of skilled employee | Scale 0 and 1: 0=no; 1=yes |
|               | X2        | Reduced office space costs | Scale 1-3: 1=low; 3=high |
|               | X3        | Improved productivity | Scale 1-3: 1=low; 3=high |
|               | X4        | Reduced turnover and absenteeism | Scale 1-3: 1=low; 3=high |
|               | X5        | Improved customer satisfaction | Scale 1-3: 1=low; 3=high |
|               | X6        | Reduced traffic congestion and environmental impacts | Scale 1-3: 1=low; 3=high |
|               | X7        | Employment opportunities for aging and handicapped people and employees’ work-life balance | Scale 1-3: 1=low; 3=high |
| Appropriateess Level | X8        | AWA is supported at all levels of organization | Scale 1-3: 1=low; 3=high |
|               | X9        | Degree of equal promotional opportunity for distributed workers | Scale 1-3: 1=low; 3=high |
|               | X10       | Level of trust between managers and their employees | Scale 1-3: 1=low; 3=high |
| Overcoming Level | X11       | Level of interaction/communication needed to perform the work | Scale 1-3: 1=low; 3=high |
|               | X12       | Degree of sequential work process vs. reciprocal work process | Scale 1-3: 1=reciprocal; 3=sequential |
|               | X13       | Degree of autonomy for work (work scheduling, decision prerogatives, etc.) | Scale 1-3: 1=low; 3=high |
|               | X14       | Level of clarity of defined deliverables | Scale 1-3: 1=low; 3=high |
|               | X15       | Required physical presence at the central place of work to be able to access specific technology, equipment, or live interpersonal response | Scale 1-3: 1=low; 3=high |
| Employee      | X16       | Employees’ level of preference for AWA | Scale 1-3: 1=low; 3=high |
|               | X17       | Employees’ level of self-sufficiency to work | Scale 1-3: 1=low; 3=high |
|               | X18       | Employees’ level of familiarity with ICT | Scale 1-3: 1=low; 3=high |
|               | X19       | Employees’ work experiences with flexible work style | Scale 1-3: 1=low; 3=high |
| Facilities    | X20       | Provision of ICT support | Scale 1-3: 1=low; 3=high |
|               | X21       | Building maintenance, cleaning, alternative workplace services, etc. | Scale 1-3: 1=low; 3=high |
|               | X22       | Utilities, furniture, business equipment, office set-up, etc. | Scale 1-3: 1=low; 3=high |
| Managerial issues | X23       | Results-based performance evaluation method in practice | Scale 1-3: 1=does not exist; 2=exists but not actively in practice; 3=exists and actively in practice |
|               | X24       | Virtual teamwork in practice within the organization | Scale 1-3: 1=does not exist; 2=exists but not actively in practice; 3=exists and actively in practice |
|               | X25       | Clear policy/guideline provision for AWA | Scale 1-3: 1=does not exist; 2=exists but not actively in practice; 3=exists and actively in practice |
| Outputs       | Y1        | AWA type | Scale 1-3: 1=hoteling; 2=group address; 3=shared office; 4=satellite office; 5=home office; 6=virtual office |
|               | Y2        | Overall satisfaction with the adoption | Scale 1-3: 1=less satisfied; 3=highly satisfied |

3. Readiness Level Assessment Indicators (RLAI)

On the basis of Roger’s innovation attributes (Roger, 1995) and Leavitt’s model of organizational subsystems
(Leavitt, 1965), Kim and Juan have proposed a framework and readiness level assessment indicators (RLAIs), for assessing the extent of an organization’s readiness for adoption of an AWA, as depicted in Table 1. (Kim & Juan, 2011). The RLAIs are expected to effectively assess the readiness of the organization’s for adopting an AWA.

Through telephone interviews, conference calls, and email questionnaires, the RLAIs are used to collect a total of 64 real adoption cases from 19 large high-tech companies that have already adopted one or more of the six AWA types: hoteling, group address, shared office, satellite office, home office, and virtual office. Twenty five assessment variables (X1-X25) are identified to assess the readiness level of the participating companies as the inputs, and two items are designed to collect the adoption outputs, namely, the actual AWA type selected along with the satisfaction level denoted as Y1 and Y2, respectively.

4. ANN-based Decision Support Model

4.1 Decision support process

Decision makers can assess the readiness of an organization to adopt an AWA using the RLAI framework as shown in Table 1. According to the results of the readiness assessment, the ANN-based decision model also suggests the appropriate AWA type and the anticipated satisfaction level. As depicted in Fig.1., a five-step decision process is developed to assist facility managers in assessing the readiness and obtaining the decision support.

Step 1: AWA consideration

Consideration of the AWA adoption starts by gathering information on the organization's objectives. If the facility managers cannot clearly identify the expected benefits of adopting AWA, then their organizations are not yet ready for an AWA. In this case, the facility managers should identify clear objectives of adopting an AWA to continue using this system.

Step 2: AWA readiness assessment

On a three-point Likert scale ("1" = relatively low, "2" = medium, "3" = relatively high), the facility managers are requested to rate their organizations' existing readiness condition. The participating organization's readiness levels are assessed along with the three important objectives of AWA adoption identified in Step 1 on the basis of the inputs of the RLAI framework.

Step 3: ANN operation process

Out of the 64 AWA adoption cases collected, 80% of the data is used for training the ANN model, and the remaining 20% is reserved for testing the ANN model. Therefore, 52 cases are stored in the ANN, and 12 cases are reserved for testing. The ANN operation process includes ANN setup, training, and testing cases from the database. The ANN operation process is described in detail in a later section.

Step 4: ANN output

The performance of the ANN model is commonly evaluated by comparing the actual and the desired outputs in the testing sets. The initial outputs obtained using an ANN-based decision model demonstrate the prediction results, including suggestions for the appropriate AWA type along with the anticipated satisfaction level.

Step 5: ANN model validation

As the first validation step, the actual outputs and the predicted outputs are compared in Step 4. As the second validation step to test the ANN-based model's potential in dealing with the decision context of this research, the case-based reasoning (CBR) technique is adopted for the model validation. By calculating the percentage similarity based on the nearest neighbor approach, CBR can indicate the similarity between the stored cases and the newly input cases.

![Fig.1. ANN-Based Decision Support Process](image-url)
4.2 ANN method

An ANN is a directed graph composed of nodes, which are sometimes referred to as units or neurons, and connections between the nodes (Zeidenberg, 1990). The human brain is composed of a very large number of neurons that are massively interconnected. ANN is a simplified model of the human brain, and it mimics the human brain by learning knowledge and storing the learned knowledge within neuron connection weights (Giudici, 2003). Over the last few years, the ANN methodology has been widely accepted to solve problems in business, and ANN has become one of the most highly parameterized models and has attracted considerable attention (Hand et al., 2001).

ANN is often introduced when there are problems of prediction, classification, or control for several reasons. The first reason is the ANN's level of sophistication (Yang, 2010). Even though linear modeling has been used commonly in various modeling domains because of the fact that linear models have well-known optimization strategies (Hill & Lewicki, 2007), there are many real business situations where the linear modeling approach is not valid or appropriate. An example would be a situation in which it is necessary to derive meaning from complicated or imprecise data. ANN is a very sophisticated modeling technique that is capable of modeling complex functions and can be used for extracting patterns and detecting trends that are too complex to be noticed by linear modeling (Hill & Lewicki, 2007). With advances in the technology of ANN, it is possible to successfully develop nonlinear ANN models to examine different processes and relationships between the input and the output variables.

4.3 Network architecture and ANN operation

The ANN method has a robust learning capability and fairly accurate prediction ability, even if the information is incomplete, especially for the decision content of this research, which is the complex nonlinear relationships between inputs and outputs (Ling & Liu, 2004). Among the many types of ANNs, the backpropagation learning algorithm with the feedforward architecture is selected to construct the ANN model. There should be at least three layers for the backpropagation learning algorithm.

Therefore, for the network architecture in this research, as shown in Fig.2., the number of neurons in the input, hidden, and output layer are 25, 12, and 2, respectively. To prevent ANN from overtraining, it is initially started with only eight neurons in the hidden layer and is optimized with 12 neurons in the hidden layer. The EasyNN-plus software is used for training and testing the predictive performance of the ANN model for the selection of an appropriate AWA type and the estimation of the anticipated satisfaction level.

After the specific ANN architecture is designed, the learning process is begun when the input values along with desired output values are entered into the ANN input layer. ANN propagates the input pattern from one layer to the next until the output pattern is determined. When the output pattern is different from the desired output pattern, the error is calculated. The error is then propagated backwards, and the connection weights of each of the neurons are modified.

The target error can be changed to any value from 0 to 0.9 in EasyNN-plus; however, values above 0.2 usually result in an under-trained ANN. Thus, the target training error is set to 0.01, which implies that each record is within 0.01 of the actual value. The training is stopped when the average training error drops below the target error (0.008). Thus, all cases are successfully trained.

![Feedforward Architecture](image)

The seven objectives of AWA adoption denoted as X1–X7 are binary-coded ("0" = not selected or "1" = selected) since the importance among the three objectives selected by the respondents is not ranked. The readiness levels measured by the 18 different indicators are denoted as X8–X25, and they are coded into three levels ("1" = relatively low, "2" = medium or "3" = relatively high). Different AWA types, denoted as Y1, are coded into six levels ("1" = hoteling, "2" = group address, "3" = shared office, "4" = satellite office, "5" = home office, and "6" = virtual office). Finally, the satisfaction levels, denoted as Y2, are coded into three levels ("1" = less satisfied, "2" = satisfied, and "3" = highly satisfied).

5. Predictive Performance and Model Validation

5.1 Results

Fifty-two of the 64 cases of high-tech companies are randomly selected to be used as inputs. The testing data set consisting of 12 cases is used for evaluating the ANN model's predictive performance. Its performance is validated by comparing the predicted values of ANN for the AWA type selection with six levels, denoted as Y1, and the anticipated satisfaction with three levels, denoted as Y2, with the actual corresponding values in the testing set. First, the predictive performance of the ANN is evaluated to see how accurately it can classify the AWA type selected by the high-tech companies.
The other measure is its ability to correctly predict the satisfaction level reported by the participating high-tech companies.

Table 2. ANN Model Predictions and Model Percentage Error (PE)

| Twelve Testing Cases | Actual Values | ANN Predictions | PE of Y1 | PE of Y2 |
|----------------------|---------------|-----------------|----------|----------|
|                      | Type Selection | Satisfaction Level (Y2) | Type Selection | Satisfaction Level (Y2) |     |
| C6                   | Hoteling      | Level 1          | Hoteling    | Level 1          | 0.00%  |
| C7                   | Hoteling      | Level 3          | Hoteling    | Level 3          | 0.00%  |
| C14                  | Group Address | Level 3          | Group Address | Level 3       | 0.00%  |
| C16                  | Group Address | Level 3          | Group Address | Level 3       | 0.00%  |
| C20                  | Shared Office | Level 3          | Satellite Office | Level 2  | 25.00%  |
| C24                  | Shared Office | Level 3          | Hoteling    | Level 3          | 66.7%  |
| C33                  | Satellite Office | Level 3       | Satellite Office | Level 3 | 0.00%  |
| C36                  | Satellite Office | Level 3       | Satellite Office | Level 3 | 0.00%  |
| C43                  | Home Office   | Level 3          | Home Office  | Level 3          | 0.00%  |
| C46                  | Home Office   | Level 3          | Home Office  | Level 3          | 0.00%  |
| C61                  | Virtual Office | Level 3          | Virtual Office | Level 3 | 0.00%  |
| C64                  | Virtual Office | Level 2          | Virtual Office | Level 2 | 0.00%  |
| Prediction Accuracy  | 83.3%         | 91.7%           |           |           |

The result of the ANN model prediction, as shown in Table 2., illustrates that there are relatively reliable predictions with only slight differences between the ANN predictions and the actual values of the testing data set. To measure the amount of error, a relative measure of accuracy is used for validating the predictions of the ANN model using Equation 1.

\[
PE = \frac{1}{M} \sum_{i=1}^{M} \frac{(AV_i - PV_i)^2}{\max(AV_i, PV_i) / N}
\]  

where \( PE \) denotes the percentage error of cases; \( AV \) and \( PV \) represent the actual value and the predicted value for \( M \) cases, respectively.

Table 2. also displays the percentage error and the prediction accuracy of the ANN model in the testing set. The overall prediction accuracy of the ANN in the training set is 100%, indicating that the ANN model perfectly learned the training set of the high-tech companies. In the testing set, the overall prediction accuracy is slightly lower: the ANN can correctly classify 10 out of the 12 AWA type selections, yielding 83.3% accuracy. Further, it can correctly classify 11 out of the 12 satisfaction levels, yielding 91.67% accuracy. The average percentage error is 7.64% for type selection and 2.78% for satisfaction level.

5.2 Model Validation

As the first model validation step, the performance prediction of the ANN model is commonly evaluated by comparing the actual and the desired outputs in the testing sets. When the trained ANN shows good prediction accuracy for the testing data that the ANN has never seen before, it can be concluded that the ANN is validated. For its second model validation step, this research adopts the CBR technique to compare the prediction accuracy of the ANN with that of CBR. CBR is a problem-solving technique in which past cases and experiences are re-used to find a solution to particular problems. The CBR technique is similar to the expert judgment approach because it can capture some general knowledge from a new experience (Shin & Han, 2001). Some research has also proved that CBR can be an effective prediction method for complicated problems (Wang et al., 2008). By calculating the percentage similarity based on the nearest neighbor approach, CBR can classify the similarity between the stored cases and the newly input cases, as shown in Equation 2. That is, every attribute in the input case is matched with its corresponding attribute in the stored case, and the decision maker can easily acquire the prediction result from the information of these stored cases.

\[
\text{Similarity}(T,S) = \frac{1}{F} \sum_{i=1}^{F} \left[ W_i \cdot \left( 1 - \frac{\sqrt{1 - T_i - S_i}}{\max(T_i, S_i)} \right) \right]
\]  

where \( W_i \) denotes the weight of feature \( i \), \( T \) represents the target case, and \( S \) refers to the source case. \( F \) denotes the number of attributes in each case, and \( i \) represents an individual feature from 1 to \( F \).

The training set consisting of 52 cases is stored in the case base, and these data are used for calculating the percentage similarity and retrieving a similar case on the basis of the percentage similarity. As shown in Table 3., the stored cases column indicates cases selected from the stored cases (training cases) on the basis of the highest percentage similarity among all the 52 cases.

Table 3. also shows that the CBR model can correctly classify 10 out of the 12 AWA type selections, yielding 83.3% accuracy. This prediction accuracy of the CBR model with respect to the type selections (Y1) is the same as that of the ANN model. The CBR model can also correctly classify 5 out of the 12 satisfaction levels, yielding 58.33% accuracy, which is considerably lower than that of the ANN model.

Comparing the prediction accuracy in terms of the percentage error of the ANN model and the CBR model, the authors find that the average percentage errors of the ANN model for predicting Y1 and Y2 are 7.64% and 2.78%, respectively, whereas the average percentage errors of the CBR model for predicting Y1 are...
Table 3. CBR Model Results

| Target Cases | Stored Cases | Percentage Similarity | CBR Prediction Error |
|--------------|--------------|-----------------------|----------------------|
| C6           | C4           | 82.00%                | Correct, Incorrect   |
| C7           | C27          | 91.33%                | Incorrect, Incorrect |
| C14          | C18          | 96.00%                | Correct, Correct     |
| C16          | C13          | 98.00%                | Correct, Correct     |
| C20          | C22          | 82.67%                | Correct, Incorrect   |
| C24          | C49          | 90.67%                | Incorrect, Correct   |
| C33          | C32          | 86.67%                | Correct, Correct     |
| C36          | C41          | 83.33%                | Correct, Incorrect   |
| C43          | C44          | 92.00%                | Correct, Correct     |
| C46          | C45          | 93.33%                | Correct, Incorrect   |
| C61          | C60          | 98.67%                | Correct, Correct     |
| C64          | C63          | 96.67%                | Correct, Correct     |
| Average      |              | 90.95%                | 83.33%, 58.33%       |

and Y2 are 8.89% and 15.28%, respectively. Moreover, the prediction accuracy of the ANN models for Y2 is 91.67%, whereas that of the CBR models for Y2 is 58.33%. Therefore, it is validated that the ANN model is more effective and robust in terms of the predictive performance than the CBR model in this research.

6. Conclusion and Future Research

In this research, the authors developed the decision support process that assists facility managers in assessing readiness and obtaining decision support. There could be three possible actions that facility managers take for the success of an AWA to be more competitive in business.

The first action is the adjustment in the appropriateness level and the overcoming level by transformation and innovation when the situation of the organization is not yet appropriate for the targeted AWA type given the objectives.

The second action is that the organization can advance to the AWA type most aligned given the organizations readiness level even if the type does not match their initially prioritized benefits.

The final action is a combination of the two actions mentioned above. For instance, while adjusting each level, the organization can change the AWA type to the most achievable one.

Moreover, the ANN-based decision model validated by using the CBR-based model allows facility managers to predict an appropriate AWA type and the anticipated satisfaction level considering their organization’s objectives and the current readiness level. The robust predictive performance of the ANN model shows that the main factors or key determinants have been correctly identified in the RLAI framework and can be used for predicting the appropriate AWA type and the anticipated satisfaction level of the AWA adoption at high-tech companies. With 64 adoption cases, the ANN-based decision model shows a more accurate prediction of the actual values than the CBR-based model.

The scope of this research is limited to the initiation stage and the adoption stage only. In the future, it will be necessary to extend the scope to the next implementation stage, where a detailed feasibility study including cost estimation and risk analysis for the final adoption decision is conducted. In future research, on the basis of a relatively large sample of AWA adoption cases from other industries, more efforts will be directed at the development of decision support systems that can provide even more accurate and solid predictions regarding AWA adoption decision issues as well as measuring the performance of the distributed workers.

Acknowledgement

This work was supported by a grant from the Kyung Hee University (KHU-20100689) and National Taiwan University of Science and Technology (NTUST). The authors are grateful to the reviewers and the editor for their valuable comments and advice.

Reference

1) Anjum, N., Ashcroft, R. and Paul, J. (2004) Privacy in the workplace design. The Design Journal, 7(1), pp.27-42.
2) Belanger, F. and Collins, R.W. (1998) Distributed work arrangement: a research framework. The Information Society, 14(2), pp.137-152.
3) Gilleard, J.D. and Rees, D. (1998) Alternative workplace strategies in Hong Kong. Facilities, 16(3-4), pp.123-137.
4) Giudici, P. (2003) Applied Data Mining: Statistical Methods for Business and Industry. New York. NY: Wiley.
5) Fritz, M.B., Narasimhan, S. and Rhee, H. (1996) Adoption of Remote Work Arrangements: An Initial Analysis. 29th Annual Hawaii International Conference on System Sciences (HICSS-29) IEEE, 3, pp.118-127.
6) Ha, M., Kim, J., Je, H. and Min, B.H. (2002) Office Environmental Satisfaction: Focusing on Personal and Common Spaces. Journal of Asian Architecture and Building Engineering, 1(2), pp.165-170.
7) Hand, D., Mannila, H. and Smyth, P. (2001) Principles of Data Mining. Cambridge, MA: The MIT Press.
8) Hill, T. and Lewicki, P. (2007) STATISTICS Methods and Applications. Tulsa, OK: StatSoft.
9) Johnson, R.M. (2009) “Telework Trendlines 2009: A Survey Brief by World at Work”, February, available at http://www.workingfromanywhere.org/news/Trendlines_2009.pdf (accessed 8 April 2013).
10) Kaczmarczyk, S. and Murtough, J. (2002) Measuring the performance of innovative workplaces. Journal of Facilities Management, 1(20), pp.163-176.
11) Kawai, Y. and Shiozaki, Y. (2005) Physical Environment of Connecticut State Government Teleworkers. Journal of Asian Architecture and Building Engineering, 3(2), pp.327-334.
12) Kim, G.H., An, S.H. and Kang, K.I. (2004) Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning. Building and Environment, 39(10), pp.1235-1242.
13) Kim, J.H. and Juan, Y.K. (2011) High-tech companies’ readiness assessment for alternative workplaces. African Journal of Business Management, 5(28), pp.11476-11486.
14) Kim, J.H., Kim, S.S., Yang, I.H. and Kim, K.W. (2008). A design support system for effective planning of the integrated workplace performance. Building and Environment, 43(7), pp.1286-1300.
15) Leavitt, H.J. (1965) Applied organization change in industry: Structural, technological, and humanistic approaches. Boston, MA: Rand McNally.

16) Ling, F.Y.Y. and Liu, M. (2004) Using neural network to predict performance of design-build projects in Singapore. Building and Environments, 39(10), pp.1263-1274.

17) McGregor, W. (2000) The future of workspace management. Facilities, 18(3/4), pp.138-143.

18) Ndubisi, N.O. and Kahraman, C. (2005) Teleworking adoption decision-making processes: Multinational and Malaysian firms comparison. The Journal of Enterprise Information Management, 18(2), pp.150-168.

19) Qu, X., Zhang, X., Izato, T., Munemoto, J. and Matsushita, D. (2010) Behavior Concerning Choosing Workstations in Non-territorial Offices. Journal of Asian Architecture and Building Engineering, 9(1), pp.95-102.

20) Rogers, E.M. (1995) Diffusion of Innovations. New York, NY: Free Press.

21) Roper, K. and Kim, J.H. (2007) Successful distributed work arrangements: a developmental approach. Journal of Facilities Management, 5(2), pp.103-114.

22) Saji, M., Matsumoto, Y., Naka, R. and Yamaguchi, S. (2006) A study of boundary areas in office space. Journal of Asian Architecture and Building Engineering, 5(1), pp.45-52.

23) Shin, K.S. and Han, I. (2001) A case-based approach using inductive indexing for corporate bond rating. Decision Support System, 32(1), pp.41-52.

24) Venkatesh, A. and Vitalari, N.P. (1992) An emerging distributed work arrangement: an investigation of computer-based supplemental work at home. Management Science, 38(12), pp.1687-1706.

25) Wang, H.J., Chiu, C.W. and Juan, Y.K. (2008) Decision support model based on case-based reasoning approach for estimating the restoration budget of historical buildings. Expert Systems with Applications, 35(4), pp.1601-1610.

26) Yang, I.H. (2010) Development of an Artificial Neural Network Model to Predict the Optimal Pre-cooling Time in Office Buildings. Journal of Asian Architecture and Building Engineering, 9(2), pp.539-546.

27) Zeidenberg, M. (1990) Neural Network in Artificial Intelligence. New York, NY: Ellis Horwood.

28) Zhang, X., Munemoto, J., Yoshida, T., Matsushita, D. and Izato, T. (2011) Comparison of Workers' Stay and Movement in Territorial and Non-territorial Workplaces: An Analysis Using a UWB Sensor Network. Journal of Asian Architecture and Building Engineering, 10(2), pp.335-342.