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Research Article

Automated Discovery and Utilization of Tacit Knowledge in Facility Layout Planning and Optimization

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Abstract

This paper puts forth a novel methodology for facilities layout planning and optimization, where the fitness evaluation of layout alternatives is automatically performed by employing an artificial neural network trained to preferences of the domain experts. The inherently uncertain, unstructured, and often tacit nature of facilities layout design preferences, constraints, and fitness objectives demands the use of domain experts for the fitness evaluation of layout alternatives, which is a resource-intensive process. Indeed, the usual unavailability of domain experts in a timely or economical manner highlights the need for resorting to the use of some intelligent and effective automation technique in this important domain. In order to test the key novel ingredient of the proposed approach, a variety of artificial neural networks are trained on a large data set containing both qualitative and quantitative fitness values of layout alternatives, as well as subjective rankings by a seasoned domain expert utilizing the knowledge of the application domain. Simulation results strongly support the viability of the proposed idea. Such an automated approach to fitness evaluations of layout alternatives is expected to significantly increase the efficacy and efficiency of the overall facilities layout planning process. Moreover, such an approach would spur the much sought for research in decision support and expert systems in layout planning. As such, the paper also provides some very interesting and promising, albeit challenging, future research directions.

Keywords: Facilities Layout; Machine Learning; Artificial Neural Networks; Preference Discovery

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Introduction

Facilities Layout Planning (FLP) involves allocation of space to various activities based on a variety of design preferences and constraints. FLP has applications in various fields of engineering such as Industrial Facility Layout Design, Machine Layout (Moslemipour, Lee, & Rilling, 2012), Transportation and Town Planning (Saif & Imam, 2004), VLSI Design (LaPaugh, 2010), Macrocell Placement (Mir & Imam, 1996), and Architectural Floor Plan Design (J. Chung & Tanchoco, 2010). FLP involves a finite number of rectangular building blocks or modules, representing various activities or functional units such as departments, machines, rooms, cells, activities, or spaces. The objective is to optimize some fitness metric by placing all the modules on the packing space without overlaps. However, the NP-complete nature of traditional formulations of FLP means that a verifiably optimal solution cannot be known even for the modest size problems (Garey & Johnson, 1979; Sahni & Gonzalez, 1976).

The combinatorial complexity and intractability of the FLP highlights the importance of using the right preferences in the optimization process, pronouncing the value of automated preference discovery tools (A. R. Ahmad, 2005; A. R. Ahmad, Basir, Hassanein, & Imam, 2006). Furthermore, the knowledge-intensive nature, absence of accurate decision models, and unavailability of domain experts in a timely or economical fashion highlight the need for resorting to the use of automation in this important area. Indeed, researchers and practitioners call for intelligent decision support systems for rationally generating and evaluating superior solution alternatives (A.-R. Ahmad, 2013; Tasadduq, Imam, & Ahmad, 2013).

In addition, the inherently incomplete, inconsistent, imprecise, vague, unstructured as well as often tacit in nature of FLP preferences further highlights the need for automated preference discovery tools (Abdinnour-Helm & Hadley, 2000; Sait, Youssef, & Khan, 2001). The term *incompleteness* suggests the unavailability of some of the information and necessitates the use of rules of thumb and approximate reasoning. *Inconsistency* indicates the difference or conflict in the knowledge elicited from experts highlighting the problem in transforming the available information into working rules and guidelines. *Imprecision* refers to values that are imprecisely or loosely defined or measured inaccurately. *Vagueness* points towards the subjectivity in the estimate about some value or rule and underscores the impediments in appropriately interpreting the available information. *Unstructured* decision preference refers to a scenario where the structural elements of the decision situation are at least partially undefined, ill-defined, or unknown (Power, 2009). In addition, many user preferences are *tacit* in nature, as decision makers may not be cognizant of those preferences so as to specify or articulate them during the planning process. (A.-R. Ahmad, 2013; A.-R. Ahmad, Basir, Hassanein, & Imam, 2004).

As discussed, the domain knowledge in FLP is uncertain, unstructured, and tacit in character (A.-R. Ahmad et al., 2004). Conceivably, this results in huge challenges in automating the FLP process. Fortunately, there are such powerful machine learning tools as Artificial Neural Networks (ANNs) for working under such uncertainties in the domain knowledge (A.-R. Ahmad, Basir, Hassanein, & Azam, 2008). ANNs are known to be universal approximators (Funahashi, 1989). Consequently, ANNs have been successfully applied in numerous application domains (A. R. Ahmad, 2005; Hagan, Demuth, & Beale, 1996; Negnevitsky, 2011). These applications cover a wide range of areas such as, Aerospace (Z.-b. Wang, Zhai, Huang, & Yi, 2013), Automotive (Naranjo, Jiménez, Serradilla, & Zato, 2012), Banking (Akkoç, 2012), Defense (Breijo et al., 2013), Electronics (Malinowski & Yu, 2011; Misra & Saha, 2010), Financial (Bahrammirzaee, 2010), Layout Optimization (A.-R. Ahmad et al., 2008), Manufacturing (Mevawalla, May, & Kiehlbauch, 2011), Medical (Er, Yumusak, & Temurtas, 2010; Jiang, Trundle, & Ren, 2010; Qian, Winfree, & Bruck, 2011), Oil and Gas (Ak et al., 2013),

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Pattern Recognition (Cherkassky, Friedman, & Wechsler, 2012), Robotics (Lu, 2011), Speech (Dahl, Yu, Deng, & Acero, 2012), Securities (G. Wang, Hao, Ma, & Huang, 2010), Telecommunications (Hu & Hwang, 2010), Town Planning (A.-R. Ahmad, Tasadduq, & Imam, 2014), Transportation (Sun, Huang, & Gao, 2012) etc.

This paper proposes a new method for facilities layout planning and optimization, where fitness evaluation of layouts is performed in an automated manner by employing such machine learning tools as an artificial neural network trained to user preferences. The rest of the paper is organized as follows. Section 2 provides the review of the related literature. Section 3 provides the proposed solution approach. Section 4 provides detailed description of the research methodology. Section 5 provides results and discussions. Section 6 concludes the paper with some interesting and promising, albeit challenging, future research directions.

Literature Review

There is a relative dearth of published research aimed at tapping such powerful machine learning tools as ANNs for learning preferences in FLP. Here we provide a brief overview of research where ANNs have been used in layout optimization in various ways. ANNs were used to solve a quadratic assignment problem involving *n* modules to be assigned to *n* potential locations (Tsuchiya, Bharitkar, & Takefuji, 1996). ANNs have also been employed for simulating and optimizing VLSI circuits (Ilumoka, 1997). Likewise, ANN has been used for VLSI cell placement (Aykanat, Bultan, & Haritaoğlu, 1998). In addition, a neural computing approach to layout planning, design, and adjustments of a workbench has been reported by (Zha & Lim, 2003). An expert system based on artificial neural networks was implemented for facility layout construction in a manufacturing system (Y.-K. Chung, 1999b). Bidirectional Associative Memories (BAM) neural networks were used as an expert system for preliminary construction layout design (Y.-K. Chung, 1999a). Hopfield neural networks have been used in combination with simulated annealing to solve a quadratic assignment problem in architectural layout (Yeh, 2006).

As evident from the previous discussion of the available literature, ANNs have been considered a promising tool in layout optimization in various ways (A.-R. Ahmad et al., 2008; Breijo et al., 2013; Kim, Yoon, Lee, & Gatton, 2008; Patrick & Nasiru, 2013; L.-T. Wang & Lee, 2014; Yannakakis, Maragoudakis, & Hallam, 2009). However, we are not aware of any literature that has shown application of ANN in automated preference discovery of uncertain, unstructured, and tacit preferences and considerations of decision makers in FLP. In this paper, we propose a novel application of artificial neural networks based learning of user preferences in FLP in an automated manner.

Automated preference discovery in layout optimization has many useful applications in any layout planning tool or decision aid. It is to be noted that the applicability of any decision support system in layout optimization is severely inhibited by the rigid nature of quantitative fitness functions employed. It is desirable to augment such quantitative fitness evaluations with subjective fitness evaluation by experts. However, domain experts in layout optimization are very scarce and expensive resource that cannot be tied in layout ranking exercise all the time. Furthermore, it is advisable to avoid experts tied up in repeated tasks that may be deemed monotonous and mundane, resulting in loss of interest in this important task of layout ranking and evaluation. In this regard, an automated layout ranking system based on an ANN trained to uncertain, unstructured, and tacit preferences of an expert could prove a highly valuable tool.

An ANN trained on the preferences of the domain expert may automatically predict the rating domain experts would assign to a new layout alternative. As such, it has the potential of mitigating the need for having domain experts present at all design and planning stages, which may even span several years. Such an automated layout ranking system could also enable generating subjective fitness values of a large number of intermediate layout solutions produced in such evolutionary optimization scheme as genetic algorithm and particle swarm optimization. Evidently, the employment of a domain expert in evaluating such a large number of intermediate solutions is infeasible due to the sheer enormity and the real-time nature of the fitness evaluation task. Conceivably, the use of such an automated layout ranking system should guarantee the integrity, efficacy, efficiency and applicability of optimization algorithms in applications where subjective ranking by experts is required.

Proposed Approach

A thorough literature review suggests that no known efforts have been directed towards automated learning of user preferences in FLP. We propose to formalize the automated learning of user preferences in the pre-planning phase of layout design through training of an ANN and, subsequently, employing the trained ANN for fitness evaluation of layout alternatives generated in any automated layout optimization process.

Soliciting user preferences is the first and most important step in FLP, as these preferences would help develop the layout fitness function. Since user preferences are usually qualitative, quantification of these preferences will be quite difficult if not impossible. For example, a user may ask for a “large” living room in his/her house but may not be able to articulate and verbalize the meaning or specifics of “large”. In addition to this inherent uncertainty, the task of extracting knowledge from users will be expensive and time consuming.

ANNs are useful in dealing with intangible and unarticulated information usually generated in such subjective and uncertain environments as FLP (A.-R. Ahmad et al., 2004). The ability of ANNs to learn from historical cases or from rankings of layout alternatives by decision-makers could automatically furnish some domain knowledge and even design rules, thus eluding the tedious and expensive process of knowledge acquisition, validation, and revision.

In order to incorporate subjective and tacit user preferences so as to effectively augment the traditional layout optimization and planning process, we propose the following novel methodology. First, the fitness rankings of a decision maker or domain expert are recorded for several layout alternatives to generate training data for an ANN. Second, an ANN is trained on this data to learn the preferences of the decision maker. Third, the trained ANN is tested to ascertain how well it predicts user rankings. An ANN is successfully trained on user preferences if it passes the testing phase. Otherwise, there may be a need for tuning one or more parameters of ANN and repeating the training phase.

Once successfully trained, the ANN can automatically predict the fitness values the decision maker would assign to any new layout alternatives or intermediate solutions generated by the automation process without any imminent need for direct user intervention. The subsequent section provides the methodology we adopted to test the novel component in this proposed automated solution.

Research Methodology

The novel component in the proposed approach is an ANN trained on user preferences for providing automated fitness evaluations in the layout optimization process. In order to investigate the viability of this novel concept, we used a test layout design problem consisting of 25 modules, termed as H25 in literature. Problem specific data can be found elsewhere (A. R. Ahmad, 2005). The objective was to place these modules in a given space. For this test problem, layout design alternatives were generated by employing MERA algorithm using IDEAL software (Ibid.). A snapshot of the user interface of IDEAL is shown in for reference purposes. MERA was selected because it is an effective algorithm known for providing layouts with high degree of space utilization and symmetry (A. R. Ahmad et al., 2006).

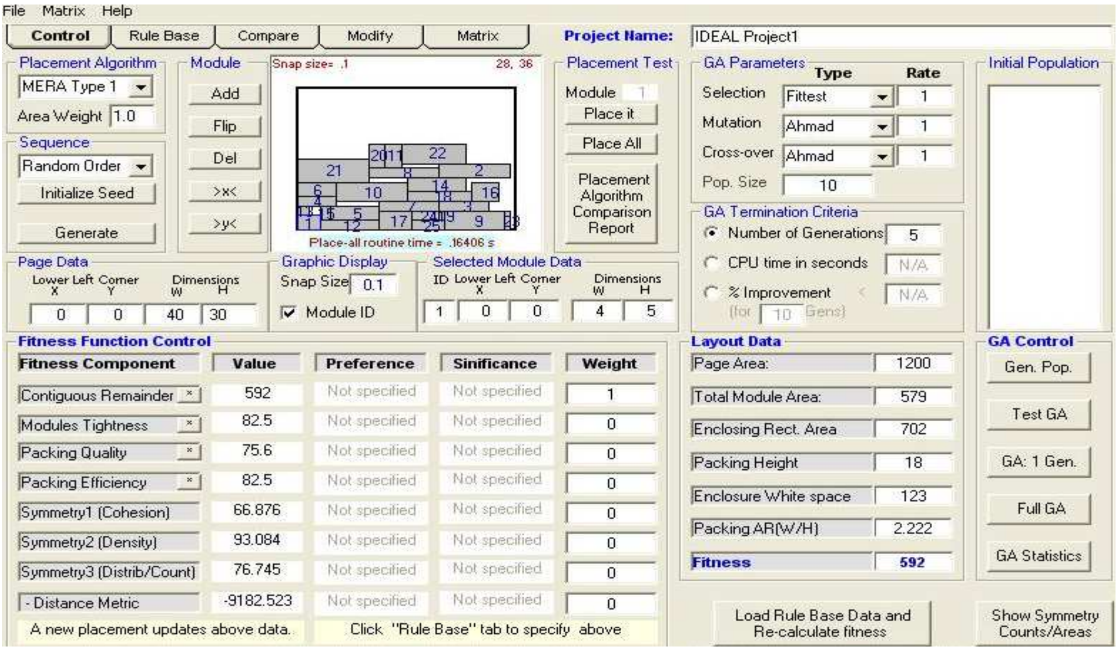

Figure 1: User Interface of IDEAL

IDEAL provides a variety of layout fitness measures, as can be seen in the bottom left part of
Figure 1**: User Interface of IDEAL**

. We used four parameters namely, Contiguous Remainder, Modules Tightness, Cohesion, and Density. The first two of these parameters measure the degree of space utilization while the later two measure the degree of symmetry and aesthetics in the layout. These parameters are continuous real numbers and their relevance in layout optimization is briefed in the following. A detailed account of these parameters are found in (A. R. Ahmad, 2005).

Contiguous Remainder (CR) provides a measure of the largest contiguous vacant portion of the packing space available for additional module placements. Higher values of CR indicate superior level of space utilization, as more contiguous space is available for packing more modules. *Module Tightness* (MT) provides a measure of how closely modules have been packed with as little trapped dead space as possible. Conceivably, a higher value of MT implies superior space utilization. *Cohesion* is a measure of symmetry in the layout and represents the extent to which modules on each side of vertical and horizontal axes of a layout configuration have the same aspect ratios (AR). A higher value of Cohesion implies superior symmetry and aesthetic appeal in the layout. *Density* is a measure of symmetry in the solution and represents the extent to which the percentage of module area on the entire layout configuration is uniform. Higher value of Density implies a higher degree of symmetry and uniformity in the amount of space occupied by modules and, in turn, a superior aesthetic value of the layout.

Using IDEAL, we produced 500 layouts by employing MERA algorithm and recorded the quantitatively computed values of the four parameters described above, which represent the four inputs of the ANN. Subsequently, without a priori knowledge of these quantitatively generated values, a domain expert provided layout rankings based on personal subjective preferences, which represent the output of the ANN.

We trained multiple feedforward backpropagation neural networks consisting of three layers; input, hidden and output. These networks were selected due to the supervised nature of learning paradigm, which aligns with the nature of the training data we are using. The four fitness measures, namely Contiguous Remainder, Module Tightness, Cohesion and Density, as described earlier, were used as inputs to the neural network and user rankings was used as the only output of the neural network. Before applying to the ANNs all the inputs were normalized such that they lie between 0 and 1.

One-Step Secant (OSS) algorithm was developed by R. Battiti in 1992 (Battiti, 1992) and is based upon secant methods. It can be considered a compromise between full secant algorithms and conjugate gradient algorithms (MathWorks, 2014). Like other secant methods, it does not require computation of Hessian at each iteration. Rather, OSS assumes that the previous Hessian was identity matrix. This not only reduces storage requirements but also the computational complexity of the algorithm. GDM is the typical steepest descent backpropagation algorithm where a momentum in the form of a filter is employed to improve convergence of the algorithm. This momentum tends to accelerate convergence while maintaining stability of the algorithm.

Results and Discussion

The parameters used for training the neural network are summarized in

Table **1** along with the performance of the two training algorithms. For both the algorithms, the neural network was trained for a maximum of 20,000 epochs. We employed the popular Mean Squared Error (MSE) as a measure of performance or convergence. Training was terminated as soon as no improvement was observed in MSE.

The number of hidden nodes in a network is critical to the network performance. A neural network with too few hidden nodes can lead to underfitting and may not be able to learn a complex task, while a neural network with too many hidden nodes may cause oscillation, overlearning/memorization, and hamper the ability for generalization (Nauck, Klawonn, & Kruse, 1997; Negnevitsky, 2011). As such, the number of neurons in the hidden layer were decided after several trial runs in which number of hidden neurons were varied from 10 to 35. The results reported in

Table **1** relate to our best experimental results. However, more formal methods for deciding the number of hidden neurons can be found elsewhere. (Stathakis, 2009)

Table 1: Parameters used for training the neural networks

Training Algorithm	No. of Neurons in Hidden Layer	Transfer Function	Learning Rate	Max. Epochs Reached	Best MSE
One step secant (OSS)	30	Tan Sigmoid	0.01	20,000	8.0843×10^{-3}
Gradient descent with momentum (GDM)	30	Tan Sigmoid	0.01	20,000	20.417×10^{-3}

A regression plot between the output of the trained neural network and the target is shown in Figure2: Regression **Plots after Training of the Neural Network**

. The value of R is 0.85439 for OSS and 0.54674 for GDM. Another such plot for the testing phase is shown in

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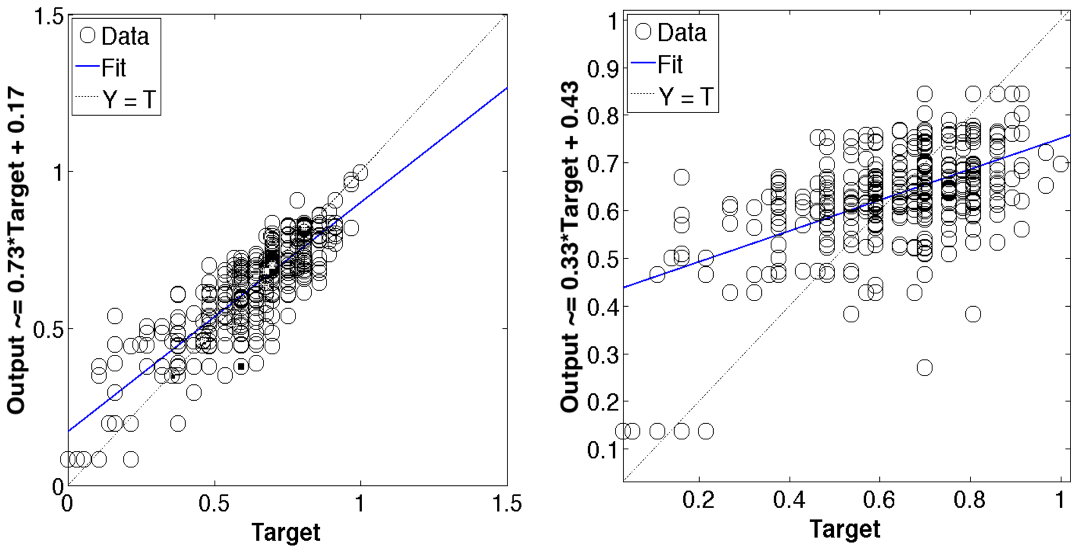
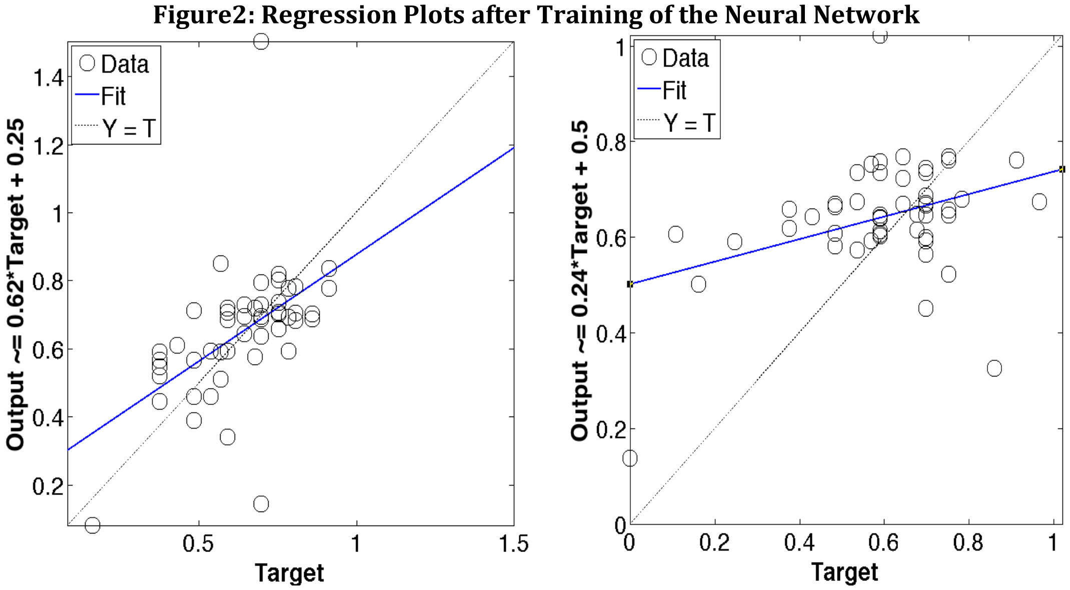
Figure3: **Regression Plots during Testing of the Trained Neural Networks**

. In this plot, the value of *R* for OSS is 0.51741 and for GDM it is 0.35539. While a regression plot combining both the training and testing phases is shown in Figure4: Regression **Plots for the Combined Training and Testing Data** with *R* = 0.80761 for OSS and *R* = 0.51962 for GDM. These regression plots and R values indicate that OSS has good training as but relatively less generalization ability. Whereas, GDM has much worse training and generalization ability.



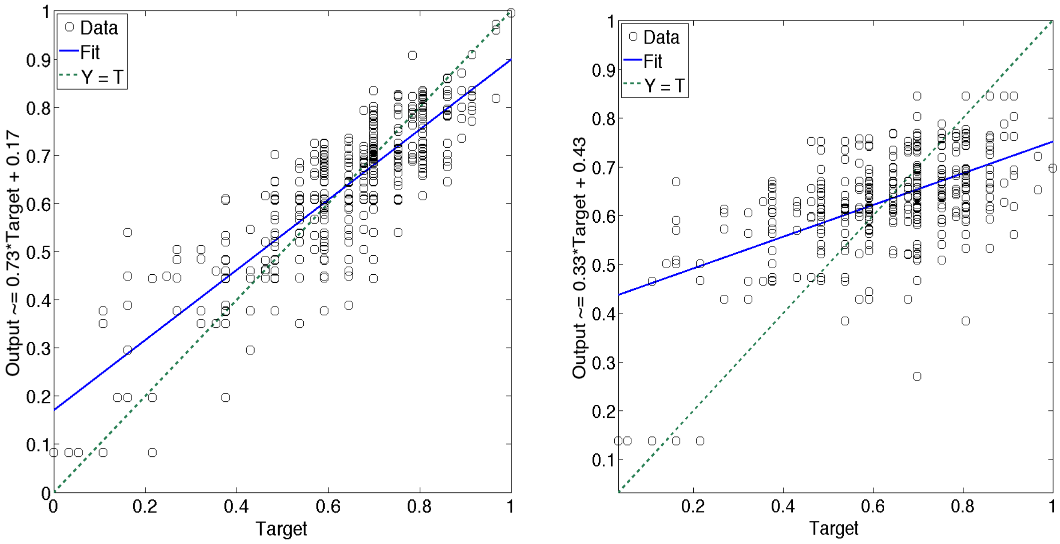
OSS GDM

Figure2: Regression Plots after Training of the Neural Network



OSS GDM

Figure3: Regression Plots during Testing of the Trained Neural Networks



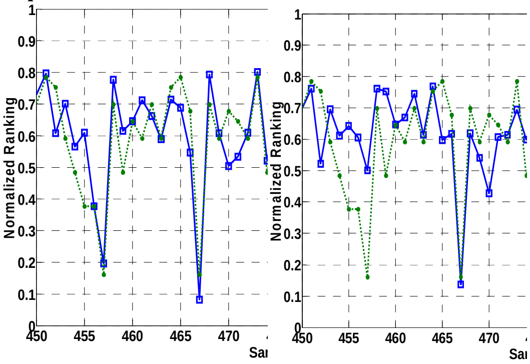
OSS GDM

Figure4: Regression Plots for the Combined Training and Testing Data

The convergence of ANN training for both the algorithms is shown in Figure 5: **Mean**

Table 1 and Figure 5: **Mean Squared Error for the two Trained Networks**

that the ANNs have learned the user preferences quite well. Moreover, it can be seen that OSS has shown better learning performance than GDM. For visual comparison purposes, we have also shown the rankings done by the trained network and the ones originally done by the domain expert in



OSS GDM

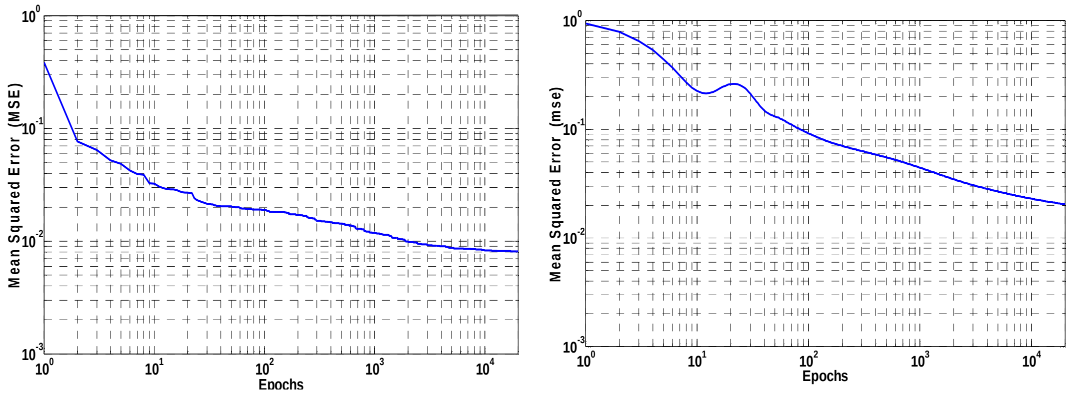
Figure 6: . This figure has been plotted using the 50 test samples. It provides strong indication that the ANNs used in our simulation studies, especially the OSS, are capable of imitating preferences of the

Squared Error for the two Trained Networks

It is evident from domain expert reasonably well. This observation is despite the fact that the regression plots for both the algorithms showed poor generalization capabilities.

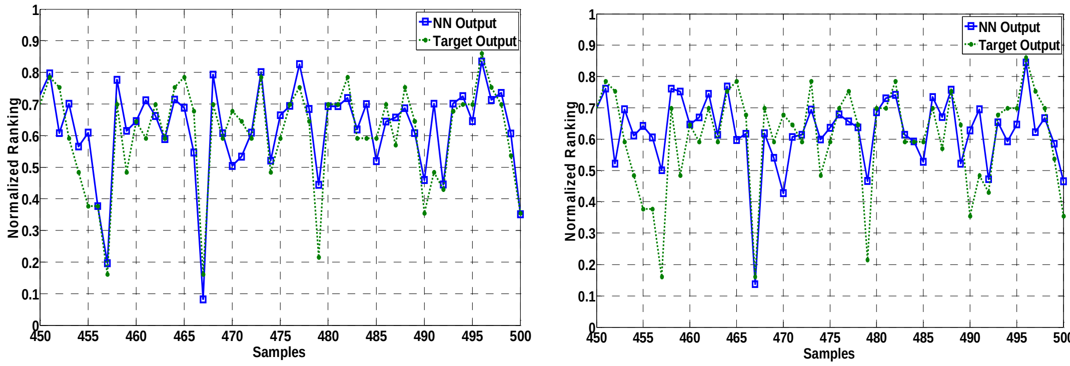
In
Figure , plots of error histograms using 20 bins for both the algorithms are provided, where the error is defined as the difference between targets and ANN outputs. These plots provide a visual impression of the shape of the distribution of the errors between the targets and the ANN outputs. By looking at Fig. 4, it can easily be deduced that in the case of OSS, the normal distribution is a reasonable model for the observed errors. In the case of GDM also, normal distribution would be the most suitable model to fit the observed errors. The low variance in this distribution is also indicative of how well the ANN have trained on training data and how well it follows on test data. It should be borne in mind that the intended application is geared towards predicting and modeling rationalization and behavior of a human expert. Indeed, modeling and predicting human behavior is a very challenging venture and imperfection in predicting

human behavior makes some prediction error inevitable.



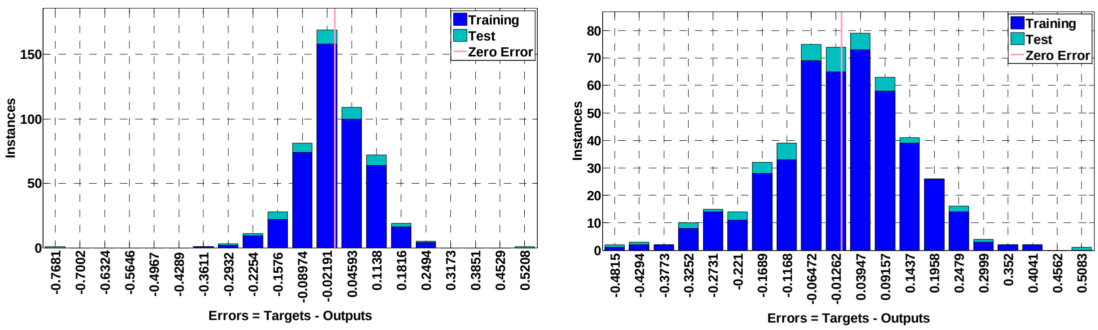
OSS GDM

Figure 5: Mean Squared Error for the two Trained Networks



OSS GDM

Figure 6: Rankings Performed by the Domain Expert compared to the two Trained Neural Networks



OSS GDM

Figure 7: Error Histograms of the two Trained Neural Networks

This research has some limitations, including the following. In general, a large representative data set is needed for a viable trained ANN. However, generating a large and representative data set in such an intricate problem domain as FLP may not be guaranteed. Indeed, the interaction of decision maker with the layout alternatives may even modify the mental model of the decision maker. Nevertheless, an online ANN may also be useful in such dynamic environments so as to learn and update preferences in an automated manner. Often a lower value of MSE is merely a result of overlearning in the ANN. Consequently, there is a need for a separate validation data set to ensure the trained ANN actually depicts a good generalization capability. Furthermore, in the proposed scheme, the ANN is trained on data generated by a single decision maker. However, often in an application of FLP of some real world consequence, multiple decision makers and users from competing stakeholder constituencies are involved in selection and ranking of layout alternatives. Such multiplicity of decision makers and stakeholders may add another level of complexity and inconsistency in the preferences. Nevertheless, an intelligent system for automating FLP process may also prove a useful tool in reconciling such competing stakeholder preferences, where ANN can play a significant role. Furthermore, such robust multi-criteria decision making tools for qualitative and non-commensurate preferences as Analytic Hierarchy Process (AHP) (Hadi-Vencheh & Mohamadghasemi) may also be utilized at the initial stage in generating preferences for the use in ANN.

Conclusions

This paper proposes a novel application of artificial neural networks in automating fitness evaluations of layout alternatives for facilities layout planning and optimization. Through simulation studies, it has been demonstrated that artificial neural networks are capable of learning well the uncertain and unstructured preferences of a domain expert in facilities layout planning. The tedious and knowledge-intensive nature of the problem as well as the unavailability of domain experts in a timely or economical fashion indicates that the proposed approach to automating the layout optimization approach can bring significant benefits to the various related application domains. Furthermore, such a tool would spur the much sought for research in decision support and expert systems in FLP. In the future, we would like to develop a metaheuristic-based layout optimization system, where layout fitness is generated automatically using an ANN trained on user rankings of preliminary layouts. We would also want to incorporate such a layout optimization system into an intelligent expert system for decision support in facilities layout planning to test the impact of this approach on the efficacy and efficiency of the overall process.

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