Information Ordering for decision support in building design

Sevil Sariyildiz, Ö. Ciftcioglu, *and* Peter van der Veer
Delft University of Technology
Faculty of Architecture, Department of Informatics *and*
Faculty of Civil Engineering, Department of Informatics
Berlageweg 1, 2628 CR Delft, The Netherlands

ABSTRACT

A systematic approach for the application of AI-based information processing for information ordering in architectural building design is described. For this purpose fuzzy associative memory (FAM) method is considered. In this system FAM is used for knowledge representation in building design concerning the functional & technical requirements information and its graded relevance to individuals concerned in the same context. A set of FAM rules having been established as a knowledge base for use, a pattern of information in the form of a fuzzy vector is fed to each FAM rule. Here, a decision support system is aimed to convey the information to the respective individuals and/or bodies involved, in a graded form, according to their capacity of involvement in the building design. By exploiting the binary logic, each FAM rule is fired in parallel but to a different degree so that each rule generates an *m*-dimensional output fuzzy vector P_i. The union of these vectors creates *m*-dimensional fuzzy decision vector D that provides the ordered information addressed to respective individuals and/or bodies mentioned. Using simulated data, a verification procedure for the performance of the approach is investigated and by means of the work, the role that artificial intelligence in architecture and building design might play, is pointed out.

1. INTRODUCTION

Building design, is one of the major activities in architecture that it involves a number of considerations and components. These include the persons in charge for the realization as well as the people/bodies concerned with respect to their due involvement and the materials used during the construction. In such a case, the information demand and correspondingly information supply can be immense and some information processing tools must be used for appropriate routing of the information flow to the prospective users the level of information being within the user's capacity of involvement. With the advancements in the building technology as well as with the related modern technologies, building design requires more comprehensive attention than that required earlier in order to meet the higher level of standards in demands. Building design involves multi-dimensional aspects to be considered with conflicting criteria. As result of this, many types of expertise are required for acceptable, if not optimal, solutions. Also, it requires flexibility to accommodate the probable emerging demands in the course of the execution of the building design project. Such unforeseen demands may naturally occur due to various reasons like new technological possibilities, new limitations imposed, for instance. In such cases, the modifications and/or additions to the existing project should be reflected to the related bodies or individuals in a well-coordinated way so that concerted actions can be taken for the efficient executions in the course of the project. For instance, a certain change in design can interest mainly the architect rather than anybody else like constructor or contractor. Therefore such information on modification should be given with different depth to different people commensurate with their involvement capacity and/or relevance to the subject matter. In the terminology of architecture, this issue is identified as information ordering.

Although the concept of a decision support system (DSS) is effectively used and developed since 80s, yet it is not quite precisely defined. Presumably, one essential reason for this is due to its utilization in different contexts and in different forms. However, it is possible to give a broad definition of this concept by referring to possible classes of decision support systems and describing the concept of a decision support system that is common to all decision support systems. However, for the present work, we can confine ourselves to the concept as its literally suggests. DSSs can broadly be divided into two distinct categories as

- DSSs based on analytical models and multi-objective optimisation, and
- DSSs based on logical models and logical inference.

The first category is especially of concern for engineering systems where the analytical models can be available from the first principles and decision situation can be formulated in analytical terms. The main decision-making task here might be conceived as the selection of one decision alternative among several others using multi-objective optimization techniques where the gravity is on the mathematical methods for decision-making.

The second category especially concerns the systems that involve design and typically require logical operations for decision-making. Here, the main task of the DDSs is to help in recognizing a logical pattern in a decision situation. For this, they use logical programming languages, expert systems, knowledge bases and other tools of artificial intelligence (AI) technology. With respect to design and decision-making processes, design is a brain activity and there are no firm rules to guide the brain activity during this process. In the context of subject matter, for a novice, the anticipated decision outcome is vague, that it contains many uncertainties due to lack of knowledge. For a knowledgeable individual or an expert the case becomes different. The quality of expert decisions might exceed considerably the quality of decisions achieved by any other means as there are no adequate models and interpretations of the parallel processing of information performed in the human mind. However, in between these two extremes, having a knowledge base prepared with the association of experts and modern computer aids, DSSs can be of great help in helping the decision-maker to get insight into the decision situation and providing details to the outlines of decision subject to consideration. Since the AI approaches are based on the activities similar to those used by brain, for logical pattern recognition type decision-making tasks, these approaches are very effective to support the design decision-making.

In particular, considering architectural building design with the associated processes, it is a complex process [Sariyildiz, 96]. To cope with the information effectively and efficiently, the modern information technology tools that are closely associated with the modern computer technology and AI methodologies should support building design decision. However, in the field of architectural building design, AI-based supports apparently are not much common compared to other means of supports in use in a computer aided architectural design (CAAD) environment. Hence, in this work the processing of building design information by means of an AI method, namely fuzzy logic, is described as a decision support for a building design. The organization of the paper is as follows. Part 2 gives a brief description of fuzzy logic in the context of information ordering and for the description of the work. Part 3 describes the information ordering with fuzzy logic and part 4 describes the detailed information ordering by sensitivity analysis as a part of the decision support for building design. Part 5 describes implementation with test data and this is followed by conclusions in part 6.

2. FUZZY LOGIC FOR INFORMATION ORDERING

2.1 . Fuzzy Logic

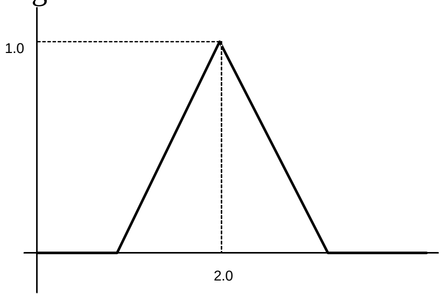
As the building design is a highly knowledge intensive problem, the most of the modern building design problems are either too complex or too ill defined to analyze with conventional methods. However, by defining the technical and functional requirements as a fuzzy set, one can perform inexact reasoning during the conceptual or creative phase of the design process with optimal information routing and design decisions.

Fuzzy set theory was introduced through [Zadeh 1965]. With fuzzy sets, a numerical value is classified into one or more linguistic labels. These labels may be discrete as well as continuous and they are coined as membership functions that represent the numerical strength of linguistic labels for the domain of classification. Since the membership functions can overlap, this results in multi-value representation of the knowledge. An input value intersects with one or more membership functions of the input classification and therefore it is attached to several linguistic labels.

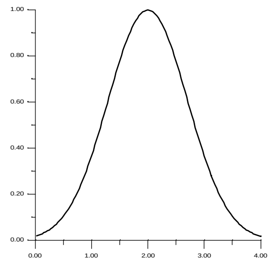
A fuzzy set A on the universe X is a set defined by a membership function μ_A representing a mapping

$$\mu_A : X \rightarrow \{0,1\}$$

where the value $\mu_A(x)$ for the fuzzy set A is called the membership value of $x \in X$. The membership value can be interpreted as the degree of x belonging to the fuzzy set A. Typical examples of membership functions for characterizing fuzzy sets in different contexts and fuzzy sets of weights representing difference in sports are shown in Fig.1a-c.



(a)



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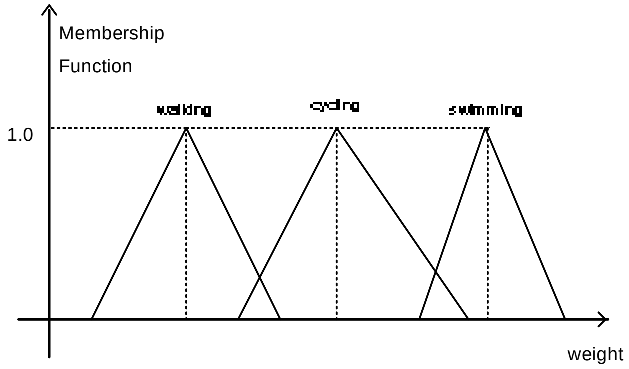

(c)

Figure 1: **Examples of membership functions for characterizing fuzzy sets in different contexts (a) triangle shaped (b) gaussian shaped (c) Fuzzy sets of weights representing difference in sports**

Before entering a fuzzy system, the information at hand is fuzzified. This is done by an input classification, matching the input value against a chosen set of linguistic labels. These labels partly overlap as shown in Fig.1c, so that a numerical value can be classified into more than one label, each with an associated membership value.

Inference is carried out with evaluating fuzzy production rules where the propagation of the fuzziness is linear with respect to arithmetic operations. Logical combinations are performed in a systematic way with certain rules known as norms. These norms have certain properties to be complied with. They should be non-decreasing in each argument, be commutative, be associative and they should have an identity value.

Since one linguistic value can be attached to several numerical values, in the context it is considered more than one rule might be triggered producing several answers. This multiple answer can be combined to reach an optimal decision or a decision region.

2.2. Fuzzy Associative Memory

Fuzzy associative memory (FAM) is a transformation described by Kosko (1992). It maps a fuzzy set to another fuzzy set. In general the FAM system includes a bank of different FAM associations. Each association corresponds to a different sequence of considerations that are expressed in numerical form by means of fuzzy logic. Therefore, the numerical data express the membership values connected to the associations. The associations are ordered systematically in a matrix form so that the numerical data constitute a matrix called FAM matrix. The FAM matrices are separated and they are accessed in parallel.

Consider fuzzy sets A and B which are multi-valued or fuzzy subsets of sets X and Y. Therefore A and B are in general in the form of a sequence of fuzzy values that they are called fuzzy vectors. The components of these vectors can be the membership values corresponding to the linguistic quantities of concern. The relationship between A and B fuzzy vectors is represented by means of FAM matrix and the transformation is performed with an operation similar to classical vector-matrix multiplication. Here the multiplication of terms is performed according to the fuzzy operational rule between the associated terms; the pairwise multiplications are replaced by pairwise minima. This fuzzy vector-matrix composition relation (Klir and Foger 1988) is denoted conventionally by the composition operator " $\circ$ ". For a given pair of bipolar row vectors (**X**, **Y**), the outer-product correlation matrix is defined by

$$\mathbf{M} = \mathbf{X}^T\ \mathbf{Y} \tag{1}$$

Similarly, we define fuzzy Hebb matrix by the minimum of the components a_i and b_j of fuzzy vectors **A** and **B** respectively, so that the encoding scheme is given by

$$m_{ij} = \min(a_i, b_j) \tag{2}$$

Accordingly, the fuzzy outer-product in matrix notation is

$$\mathbf{M} = \mathbf{A}^T \circ \mathbf{B} \tag{3}$$

Due to the similarity of this equation to correlation matrix in the statistical theory, the matrix **M** is called correlation-minimum encoding. If the vectors **A** and **B** are encoded in the FAM matrix **M**, then the FAM system exhibits perfect recall in the forward direction:

$\mathbf{A} \circ \mathbf{M} = \mathbf{B}$.

3. INFORMATION ORDERING

As the building design involves many disciplines in one way or other, it is a multidisciplinary process. A constituent part of this process as a sub-process is schematically shown by the scheme in Fig.2 where different experts from different fields contribute to this (sub)-design decision. Since the building design is a complex process, it has several consecutive such stages that form constructively the building design altogether. The stages might have also re-iterations before certain intermediate or final decisions are made. Virtually, each decision process for each stage might be represented with this generic scheme so that, the representation can be seen as a generic decision-making process that applies virtually every major stage of building design.

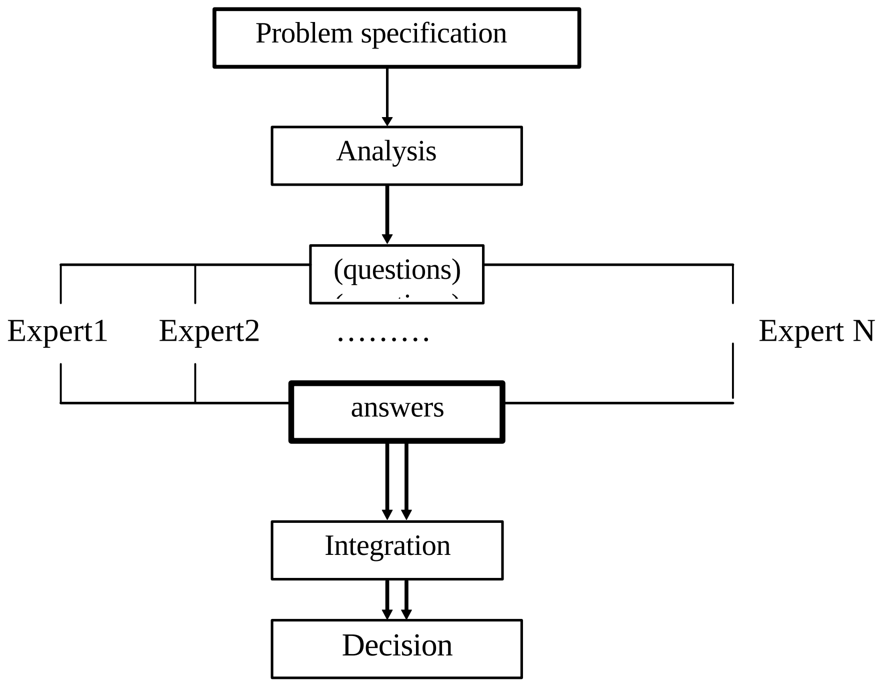

Figure 2: **Multidisciplinary decision process**

The fuzzy implementation of this concept is shown in Fig.3. The FAM bank constitutes the knowledge base representing the experts' knowledge in Fig.2. The functional and technical requirements are used as input to a FAM bank to generate outcomes to channel the fuzzy pattern information at the input to different partners participating in the building process. Among these, one can refer to architect, contractor, principal, authority, consultants, individuals, virtual head and/or representatives of organizational bodies and so on. Here, the input to the FAM matrices is the vector of functional and technical requirements, subject to information ordering. The functional and technical requirements of concern are derived from the respective criteria.

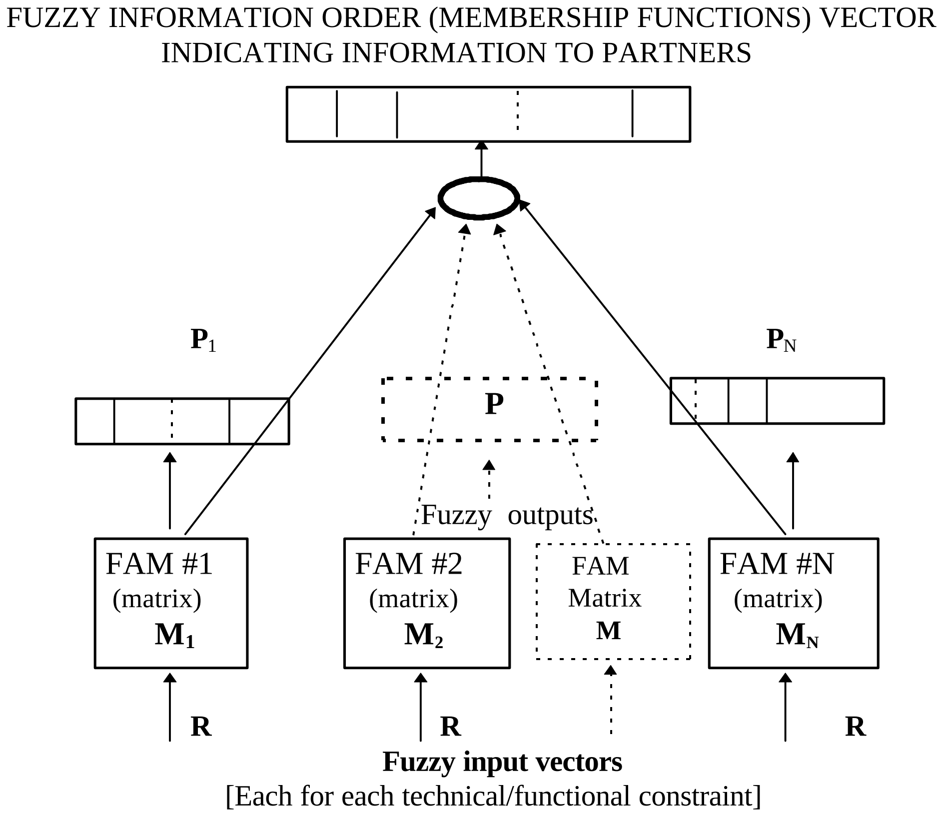

Figure 3: **FAM approach for building design decision support system**

For this implementation, the appropriate FAM matrices are established using the data subject to building design and consulting the experts available. Generic set of FAM rules having been established any architectural new information arising during the design or implementation and subject to decision-making is fed to each FAM rule in the form of a fuzzy vector **R** according to the matrix-fuzzy equation **R**° **M** = **P**.

Each FAM rule is fired in parallel but to a different degree so that each rule generates an *m*-dimensional output fuzzy vector P_i where *m* is the number of the partners. Each partner is expected to have different due information, according to his/her degree of involvement and nature of involvement capacity in the design process. The union of these output fuzzy vectors P_i creates the *m*-dimensional fuzzy vector **D** that provides the membership functions of the fuzzy sets representing of the ordered information addressed to respective partners. In other words, it represents the graded information relevance to each partner, concerning the given information in the form of fuzzy pattern vector at the input of the FAMs. To be explicit, suppose we are given a functional and/or technical requirements fuzzy vector **A** of dimension *n*. Then this vector is fed to each FAM_i of dimension $n \times m$ yielding the fuzzy vector outcome $\mathbf{P}_i$ the components of which are computed from

$$\mathbf{P}_i = \mathbf{P}_{RoM}(p_j) = \max_{i=1}^{n} [\min(a_i, M_{ij})] \qquad (4)$$

where the indices i and j are for the i-th fuzzy output vector and its j-th component, respectively; index n , indicates the number of functional and/or technical requirements. Each FAM rule is fired in parallel but to a different degree so that each rule generates an *m*-dimensional output fuzzy vector $\mathbf{P}_i$. Basically, this means each FAM rule gives a best information ordering in a graded form by the membership values. For the optimal decision of information order, all FAM outputs should be combined in a constructive way that is referred to as “information fusion”. This is performed by means of fuzzy union of all outcomes so that the union of these output fuzzy vectors $\mathbf{P}_i$ creates the *m*-dimensional fuzzy vector **D** that has the information of membership values as its components.

4. DETAILED INFORMATION ORDERING

4.1. **Sensitivity analysis**

The information ordering for building design described above reveals global information to the partners involved. That is, the outcome **D** indicates the graded relevance of the information at the input to respective due partners. However, information on which component at the input pattern is and to what extend it is important to the respective partner at the output, is not explicitly indicated. This information can be derived by means of sensitivity analysis. Sensitivity analysis investigates the effect of changes in input variables i.e., input membership values on the output variables i.e., output membership values. Therefore, this is the detailed information on information ordering we are seeking. This is basically expressed by partial derivatives of the form $\partial y_j/\partial x_i$ where y_j represents the j-th component of the fuzzy output vector and x_i represents i-th component of the fuzzy input vector. y is expressed by $y_j = f(x_1, x_2, ...,x_m)$. The relative magnitude of the partial derivative indicates the relevance of the piece of information at the input to the due partners that are represented by the fuzzy vector **D** at the output. However, since the FAM approach is based on max-min composition rule, i.e., discrete computation, the required derivatives for the sensitivity analysis cannot be obtained in this form. To obtain this information, the neural network counterpart of the FAM approach can be used where input-output relationships can explicitly be defined as continuous functions and the required partial derivatives for sensitivity analysis can readily be computed. The neural network that may be considered as the counterpart of FAM approach is the radial basis function (RBF) network. RBF networks are widely treated in literature (Haykin 1995). A brief description of RBF networks is given below.

4.2. **Radial Basis Function networks in brief**

Radial-basis function network is an example of nonlinear layered feed-forward neural networks with special pattern recognition capability. The network due to the input-output fuzzy mapping performs the most beneficial use of pattern recognition property in decision support. The network learns from examples that are prepared using an external knowledge base so that it constructs an input-output mapping in the form of information ordering. This process is termed as "training". Once this mapping is established, it responds to multi input excitations that corresponds to the technical and/or functional requirements and thereby performs the information-ordering task. Explicitly, the trained network classifies a fuzzy input pattern and provides outcome using the information gained through training. In other words, it provides outcome, compatible with the inherent knowledge base formed by training process.

In RBF network, FAM matrices are replaced by the network itself which employs the gaussian shaped activation functions as shown in Fig.1b. Here, the gaussian functions play the role of membership functions. Hence the fuzzy membership values are determined by the multivariable logic formed by the overlapping gaussians the case being similar to that formed by triangular membership functions in Fig.1c. A simple RBF network having only one output for simplicity is shown in Fig.4. The construction of a radial-basis function network in its most basic form comprises three entirely different layers. The first layer is the input layer for the introduction of the input information. The second layer is a hidden layer of radial base functions that are gaussians. The third layer is for the output that gives the global information ordering.

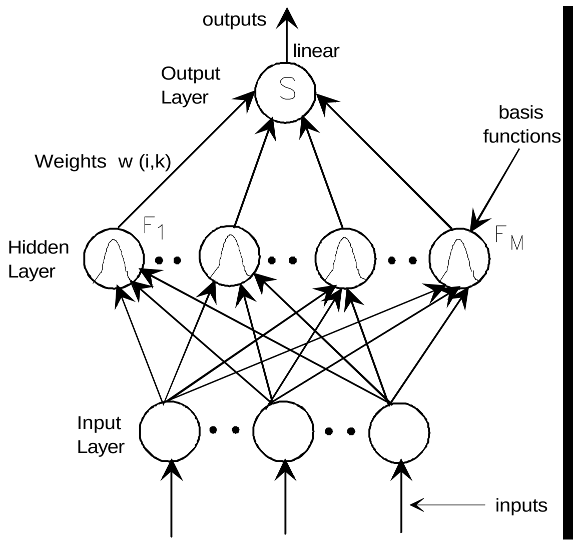

Fig.4: **Architecture of a basic radial-basis function network having only one output**

The output membership value is computed by

$$y_k(\mathbf{x}) = \sum_{j=1}^{M} w_{kj}\ \phi_j(\mathbf{x}) + \phi_0(\mathbf{x}) \qquad (5)$$

where M is the number of hidden layer nodes; k, is the index parameter for the output nodes (in figure 5 k=1); $\phi_j(x)$ is the basis function given by

$$\phi_j(\mathbf{x}) = \exp\left(\frac{\| \mathbf{x} - \eta_j \|^2}{2\sigma_j^2} \right) \qquad (6)$$

where $\mathbf{x}$ is the input vector with elements x_i ; σ, is the variance of the gaussian; η_j , is the vector determining the center of the basis function ϕ_j and has elements η_{ji} .

5. IMPLEMENTATION WITH TEST DATA

The FAM approach described is implemented using self-created test data, to test the performance of the method. The number of partners involved in the building design is taken to be five, namely architect, contractor, principal, authority, consultants and the number of technical and functional requirements is taken to be ten in order to keep the test case simple. With the data, to assess the decision-support performance of the approach is rather difficult since such an assessment requires actual data and experts for the integrity of the knowledge base. However, with the test data two fundamental AI approaches for information ordering in architectural building design, that is FAM and RBF approaches are tested and the results obtained are observed to be consistent. This observation is what one might expect due to the following reasoning. The reasoning basically is that, although the two approaches employ different paradigms, namely *fuzzy* logic and *neural* networks, their outcomes should be equivalent since in both cases the same membership function information is processed. Furthermore, concerning the knowledge base formation, FAM matrices (**M**) are formed by expert information using the input (**A**) and output (**B**) fuzzy membership vectors in the fuzzy-matrix equation $\mathbf{M} = \mathbf{A}^{\mathbf{T}} \circ \mathbf{B}$. On the other hand, in RBF network, the network is subjected to training using the same (**A**) and (**B**) fuzzy membership vectors establishing the equivalent knowledge base as the counterpart of FAM knowledge base. With respect to above reasoning, it may be noteworthy to point out that the knowledge base structures are quite different in both cases. This means, in the case the outcomes from both paradigms are inconsistent, the source of inconsistency should be identified for the reliability enhancement of the decision support. In this case, the formation of FAM matrices and the neural network training methods are the important issues. Here, particularly several neural network training algorithms can be considered and thereby appropriate training paradigm should be identified considering the peculiarity of the application.

6. CONCLUSIONS

Two AI methods, FAM and RBF, are tested for information ordering in building design. However since self-created data are used, basically the consistency of methods are investigated. The test results from both approaches are found to be reasonably equivalent. Since both methods use independent methods, RBF network approach can be used as a means for verification of the FAM approach, or vice versa. By means of this, the reliability of the outcomes from the decision support system is enhanced. This can be one strong motive for the consideration of RBF network approach next to fuzzy logic (FAM) approach in applications. This is something apart from the additional detailed information acquisition on the information ordering, by the RBF network.

The present research on AI methods for information ordering in building design, using two well-established paradigms, refers to these fundamental approaches as decision support in architecture. Seemingly, the use of AI technologies in architecture has nowadays relatively less appeal. Presumably, this can be explained with the abundance of linguistic information in architecture and lack in the available tools in dealing with this information. However, the use of AI technology is especially subject to consideration in complex design situations. In such a case, decision-making is a hard task due to the overwhelming information to be handled appropriately and then, AI technology and the associated decision support systems can be of substantial help. In this respect, the present research has pointed out and indicated the feasibility of AI technologies (*fuzzy-neural* in this case) for applications also in architecture and related fields.

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