A NOVEL APPROACH TO LIFE SPAN PREDICTION OF CONTAINER HOUSES VIA ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Nihat ATMACA
Vocational School of Technical Sciences, Gaziantep University, atmaca@gantep.edu.tr

ABSTRACT: Buildings are expected to be long-lived engineered works under usual conditions. In Life Cycle Assessment (LCA) of building analysis, Life Span is one of the most effective parameter. The aim of this study is to make the Life Cycle Assessment analysis of containers and to investigate the relationship between Life Span and consumed energy via Adaptive Neuro-Fuzzy Inference System (ANFIS) approach. The proposed model in the study focused on the construction phase of the containers to estimate total energy use for different life span years. Life span years are chosen between 5-100 years interval. It is found that energy and emission values are decreasing with the increase of life span years in container type houses. The results of the proposed ANFIS modeling approach shows very promising results. According to the results ANFIS approach is a viable tool for Life Span more accurate predictions in LCA studies.

Key words: Life Cycle Assessment, Life Span, Adaptive Neuro-Fuzzy Inference System, Containers

INTRODUCTION

Turkey is located in a very strategic region that is affected by severe natural (earthquakes, floods etc.) and man-made (civil wars) disasters. Recovery works undertaken to eliminate physical, economic, social and environmental losses caused by disasters constitute an important part of the disaster management process. The Disaster and Emergency Management Presidency of Turkey (AFAD) is a governmental organization established in 2009 to take necessary measures for effective emergency management and civil protection nationwide in Turkey. AFAD has prepared a performance indicator for the improvement of recovery capacity between 2013 and 2017 years in Turkey (Table 1) (AFAD, 2012).

Table 1 Performance indicator

Indicator	2013	2014	2015	2016	2017
Capacity of established container cities (person - cumulative)	50,555	50,555	50,555	50,555	50,555
Capacity of stocked containers (person -	19,225	32,870	32,870	32,870	32,870

cumulative)					
Number of personnel trained on recovery processes increased yearly by	58%	58%	58%	58%	58%
Repayment ratio for disaster loans extended to eligible families	40%	45%	50%	55%	60%
Yearly melting rate of increasing disaster housing stock	40%	40%	40%	40%	40%
Improving the damage assessment process	20%	20%	20%	20%	20%
Realization ratio according to number of total disaster houses in the annual programme (17,535 houses in the programme at start of 2013)	40%	45%	50%	55%	60%
Ratio of cases lost in lawsuits related to Law no.7269 finalized within the year decreased by (based on 2012 figures)	5%	10%	15%	20%	25%

According to the AFAD statistics, there is a continuing need for disaster housing stocks. The use of energy for the container houses have been increasing and can be expected to increase in the future. Therefore, the choice of the housing type is an important area for reducing energy requirements and greenhouse gas emissions.

LCA methods have been used for environmental evaluation in many industries and by many researchers to assist with decision-making for environment-related strategies and to reduce buildings' life cycle environmental impacts last decades (Singh, Berghorn, Joshi & Syal, 2011; Buyle, Braet & Audenaert, 2013).

According to ISO 14040, LCA is the investigation and evaluation of environmental impacts of a given product, system or service, over its entire life cycle.

A simplified version of LCA, life cycle energy analysis (LCEA) is used to assess the environmental impact of buildings. It focuses only on the evaluation of energy inputs for different phases of the life cycle. This methodology is applied to several studies found in the literature (Ramesh, Prakash & Shukla, 2010).

In addition to LCEA, Life Cycle Carbon Emissions Assessment ($LCCO_2A$) is used for evaluating the CO_2 emissions as an output over the whole life cycle of a building. The approach considers all the carbon- equivalent emission output from a building over different phases of its life cycle (Atmaca, 2016).

Container houses play a significant role in consumption of energy resources especially after disasters. Thus, container type housing is an important area to represent a major opportunity for reducing energy requirements and greenhouse gas emissions. This paper is the first study predicting Life Span of containers in order to make LCEA.

Fay et al. (2000) examined the primary energy use of a detached house in Melbourne, Australia. LCEA over lifespans of 0, 25, 50, 75 and 100 years were carried out for the base case and then with added insulation. Total energy consumption of the building is calculated to be 76 GJ/m^2 in 50 years of life span.

Bastos et al. (2014) showed the linkage between building design, energy use and GHG emissions. The linkage is dependent on and sensitive to climate and sociodemographic characteristics that are geographically and culturally variable. It was also shown that larger buildings have lower life cycle energy requirements and GHG emissions on a square meter basis and reverse pattern on a per person basis.

Atmaca (2016) investigated the total energy use and CO_2 emissions over 15 and 25 year lifespans for container and prefabricated houses respectively. It was concluded that operation phase energy has a major share in both LCEA and $LCCO_2$ on a per meter square basis.

There are some studies about the final energy consumption of residential buildings in Turkey. However, the studies about the life cycle energy consumption and environmental effects of container houses are limited in number and scope in literature. Meanwhile, there is currently very few studies about the final energy consumption of residential buildings in Turkey (Atmaca and Atmaca 2015). Complex real-world problems may require intelligent systems that possess human-like expertise within a specific domain, adapt themselves to changing environments, and be able to explain how they make decisions or take actions (Donald, 1986). Various artificial intelligence (AI) techniques (fuzzy logic and neural networks) have been developed and used in industrial applications (Liebowitz, 1990). This study uses such an attempt by using ANFIS to predict the Life Span of containers. The data obtained from the LCA analyses (Atmaca, 2016) is used to test and train ANFIS. The input variables used in ANFIS to estimate the Life Span of container are; Construction phase embodied energy and used area in Container Houses. Numerical results reveal a good agreement among the test, fuzzy and ANFIS results.

METHODS

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Fuzzy modeling (Jang et al. 1997) is an emerging branch of system identification. The model deals with the construction of a fuzzy inference system or 'fuzzy model'. By the way, prediction and explanation of the behavior of an unknown system or parameter can be described by a set of sample data. A fuzzy-inference system employing fuzzy 'if–then rules' can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. The fuzzy modeling or fuzzy identification studies carried out systematically by Takagi and Sugeno (1985).

The implementation of Fuzzy Logic (FL) to real applications considers the following steps (Bai et al. 2006):

(1) Fuzzification, which requires conversion of classical data or crisp data into fuzzy data or membership functions (MFs),
(2) Fuzzy inference process, which connects MFs with the fuzzy rules to derive the fuzzy output,
and
(3) Defuzzification, which computes each associated output.

Fuzzy systems can be connected with neural networks to form Neuro-Fuzzy systems which reveal advantages of both approaches. Neuro-fuzzy systems combine the FL's natural language description and NN's learning properties. Various Neuro-Fuzzy systems have been developed that are known in the literature under short names. Adaptive network-based fuzzy inference system (ANFIS) developed by Jang (Jang et al. 1997) is one of the Neuro-fuzzy systems which allows the fuzzy systems to learn the parameters using adaptive backpropagation learning algorithm (Rutkowski 2004).

Three types of fuzzy inference systems (FISs) have been widely employed in various applications:

Mamdani,
Sugeno,
Tsukamoto

The differences between these three fuzzy inference systems are due to the consequents of their fuzzy rules, and thus their aggregation and defuzzification procedures differ accordingly (Jang et al. 1997).

The Sugeno FIS is used in present study. Each rule is defined as a linear combination of input variables in a Sugeno FIS. The corresponding final output of the fuzzy model is simply the weighted average of each rule's output. A Sugeno FIS consisting of two input variables x and y, for example, a one output variable f will lead to two fuzzy rules:

Rule 1: If x is A1, y is B1 then $f1 = p1x + q1y + r1$
Rule 2: If x is A2, y is B2 then $f2 = p2x + q2y + r2$

where pi , qi and ri are the consequent parameters of the ith rule. Ai , Bi and Ci are the linguistic labels which are represented by fuzzy sets shown in Figure 1.

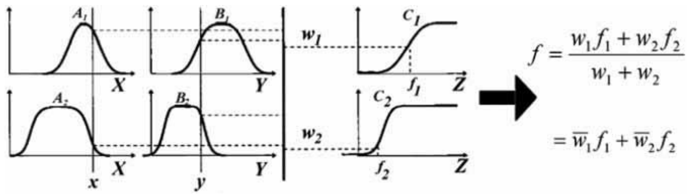

Figure 1. The Sugeno Fuzzy Model (Jang et al. 1997).

In the present study, MATLAB FL Toolbox is used for the ANFIS modelling process. Various types of MFs such as Gaussian, Gaussian combination, generalized bell-shaped, triangular-shaped and trapezoidal-shaped are used.
Life Cycle Assessment Analysis

The elementary concept of LCA is to calculate the environmental impacts of a product over different life cycle stages. LCA evaluates all the resources inputs, including energy, water and materials, and environmental loadings including CO_2 emissions and wastes of a building during different phases of the life cycle. Mathematically;

$$I = I_{\text{Extraction}} + I_{\text{Manufacture}} + I_{\text{Onsite}} + I_{\text{Operation}} + I_{\text{Demolition}} + I_{\text{Recycling}} + I_{\text{Disposal}}$$

Where I represents the life cycle environmental impact, and Ij represents the environmental impacts of jth building phase.

LCEA focuses on energy inputs to a system and $LCCO_2A$ focuses on the CO_2 equivalent emissions released from a system (Fig.3).

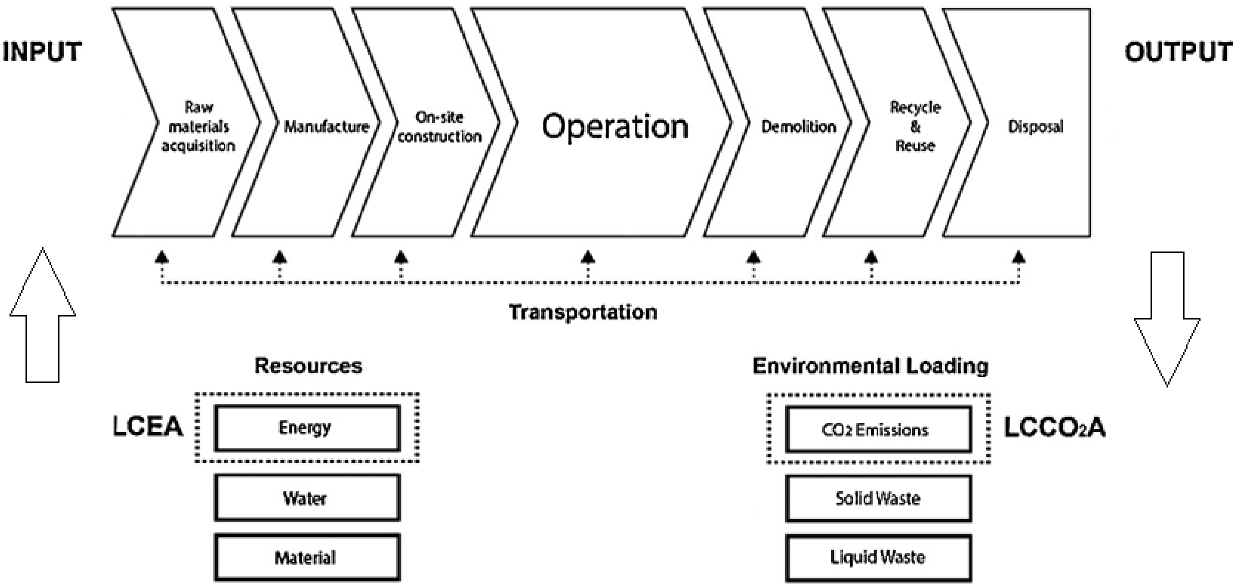

Figure 2. Basic models of LCEA and $LCCO_2A$ (Atmaca &Atmaca, 2015).

Construction, operation and demolition of buildings consumes large amount of energy and produces lots of CO_2 emissions. Predictions over energy consumption during operation phase of the building life cycles and assumptions about the end of the life span of the houses are highly uncertain. Therefore, only the construction phase is used for the energy analysis with different life span years by using ANFIS modelling process.

Technical specifications and the floor plan of the CH are presented in Table 2. The typical CH has a gross area of 20, 21 and 22 m^2 with one story, two rooms and a WC inside it.

Table 2.Technical specifications of CH

Specifications	CH
Foundation	20 cm concrete with 6x150x150 mm mesh reinforcement
Structural System	Steel profiles and wall panels
Exterior And Interior Walls	35 mm thickness sandwich plasterboard panels
Floors	16 mm thickness precast concrete panels and 3 mm PVC coatings
Roof Covering	Galvanized roller steel sheets, OSB, 80 mm thickness glass-wool
Doors	900*2100 mm steel framed for exterior door and 800*2100 mm PVC framed for interior doors
Windows	100*110 mm PVC framed with single 4 mm single glazing.
Exterior surface coatings	Sandwich plasterboard panels

Construction phase analysis

Construction phase analysis includes embodied energy (EE) and CO_2 emissions analysis. EE is defined as the total primary energy (MJ) required by the building materials during manufacturing phase (Hammond & Jones 2008).

In this study, Inventory of Carbon and Energy (ICE) Version 2.0 (Hammond& Jones 2011) is used for the calculation of primary energy requirements. The ICE includes the embodied energy, carbon and GHG (measured in grams of CO_2 equivalent, g CO_2-eq) for a large number of materials. Some important criteria were applied for the selection of energy values for the individual materials incorporated into the ICE database. This ensures the consistency of data within the inventory. One of the applied criteria is about the compliance of data with approved methodologies and standards (ISO 14040/ 44).

Table 3 Embodied energy for different types of building materials

Type of the building materials	Embodied energy

	intensity (MJ/kg)*
Concrete	0.5–1.6
Galvanized steel	35.8–39
Polymer vinly siding	11.8–120
Precast concrete element	2
Wood	9.1-14.2
Thermal and acoustic insulation	3–45
Plastic, rubber and polymer	67.5–116
Purified fly ash (PFA)	<0.1
Stainless steel	51.5–56.7
Plaster, render and screed	1.4–1.8
Reinforcing bar and structural steel	9.9–35

* Intensity values were extracted from ICE.

Life Span Prediction

Building life span is a very important variable in LCA calculations. The container house type LCA analysis with different Life Span years have been carried out. Among the analysis result database, 17 tests were used as test set and the remaining 61 tests as training set for training. The proposed ANFIS model is based on the output MF is chosen as the simplest function available which is a constant value. The structure of the ANFIS model is shown in Figure 3.

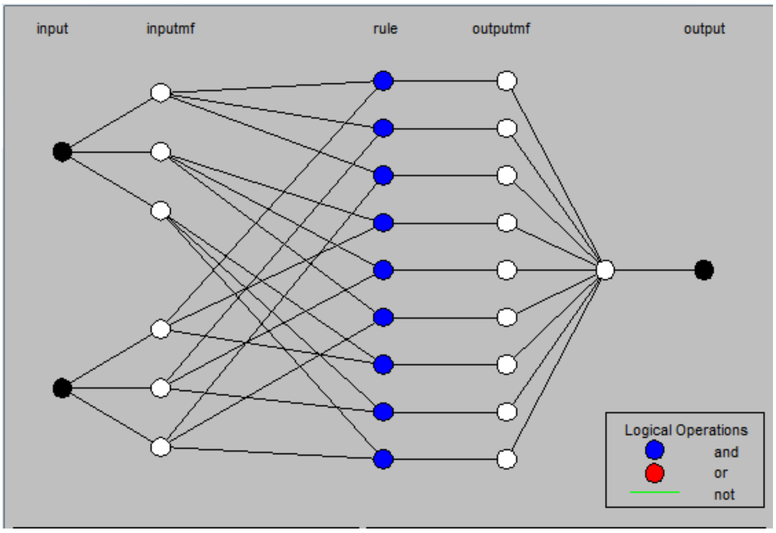

Figure 3 ANFIS Model Structure

The fuzzy inference diagram of the proposed ANFIS model is shown in Figure 4. The initial and final MFs for inputs are presented in Figure 5. The input and output surface of the ANFIS model is given in Figure 6.

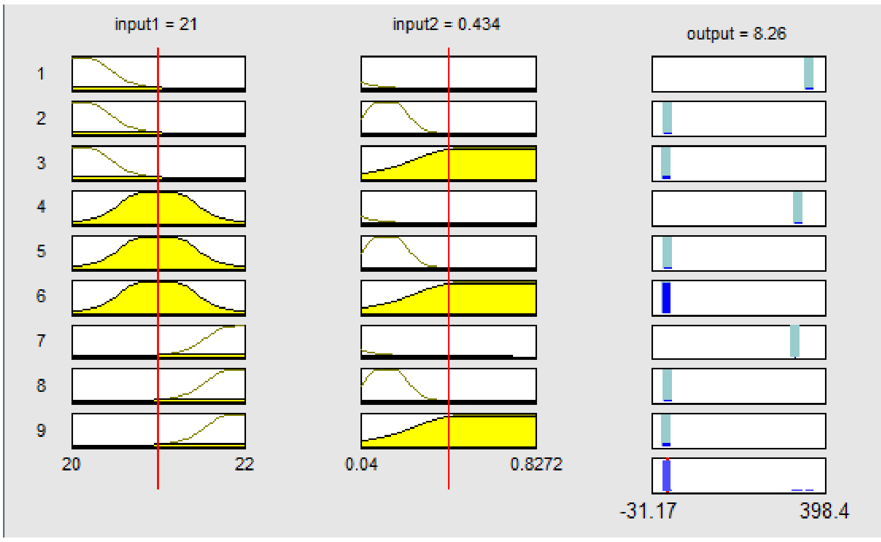

Figure 4 Fuzzy inference diagram of ANFIS model.

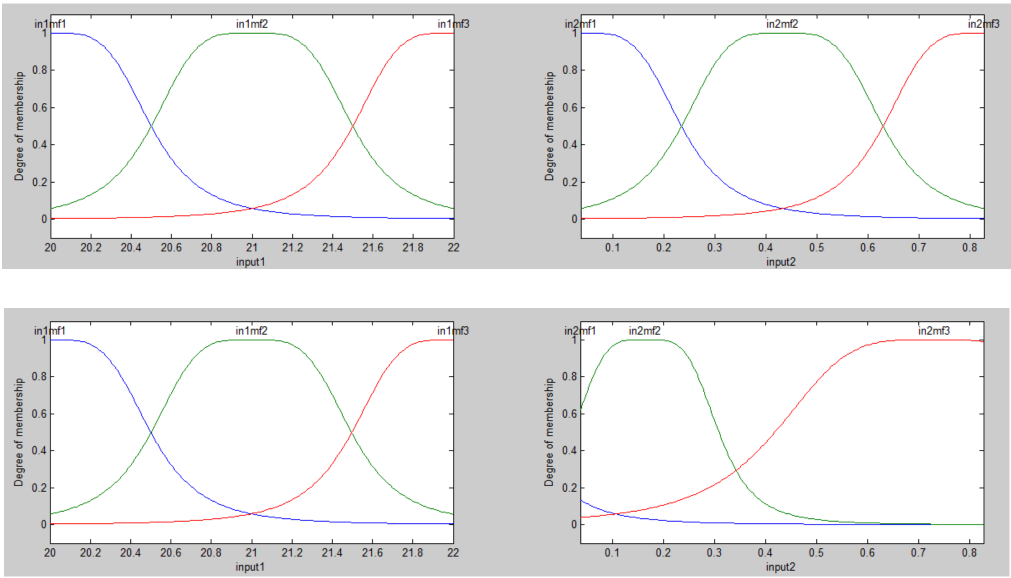

Figure 5 Initial and Final Membership Functions of Inputs

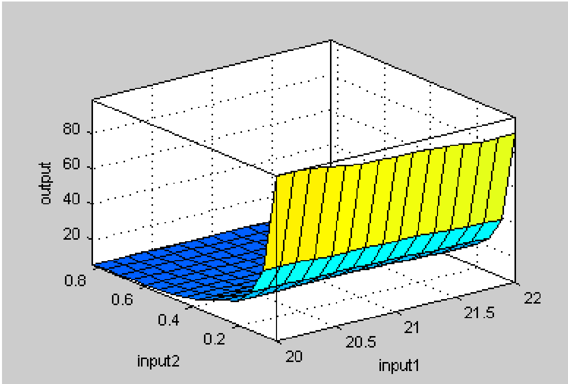

Figure 6 Output Surface of ANFIS Model

RESULTS AND FINDINGS

Life cycle analysis of container housings involves many assumptions, simplifications and uncertainties. The materials used in construction, life span, location and climatic conditions and building data of the houses has the potential to vary the findings of this study.

In Life Cycle Assessment (LCA) of building analysis, Life Span is one of the most effective parameter. The accurate prediction of Life Span has crucial importance in LCA methods. In this context, alternative methods such as soft computing techniques can be used to overcome this difficulty. This study is a pioneer work that search into the capability of neuro-fuzzy (NF) approach for the prediction of Life Span of the container houses. The actual and operational data are considered in the study. Among the 78 total data sets, 17 datas are used as test and the remaining 61 datas are used as training data sets. Sugeno type of FIS is used where each rule is defined as a linear combination of two input variables. The corresponding final output of the fuzzy model is simply the weighted average of each rule's output. The aim is to construct the ANFIS model fitting those values within minimum error for independent input variables. The results of the study show that the energy values are decreasing with increasing Life Span years (Figure 6). The rapid decrease is observed in first 5 and 10 years. The results of the ANFIS has quite satisfactory for future analyses.

CONCLUSIONS

Life Cycle Energy analysis of container houses constructed in Turkey are presented for different Life Span years. The construction phase was used for the analyses. EE and area of the houses are chosen as inputs. Fuzzy-expert rules (IF–THEN rules), membership functions and defuzzification methods are used to eliminate the complexity of the prediction of Life Span. The ANFIS approach generates rules between each input and output. The results of the proposed ANFIS model are observed to be quite accurate predictions. The outcomes of this study are quite satisfactory which may serve Neuro-Fuzzy approach to be used in LCA applications.

RECOMMENDATIONS

Further studies are needed to investigate more about the use of more comprehensive LCA methods. Hybrid analysis is generally considered the preferred approach for EE analysis due to its systemic completeness and use of reliable data. I–O-based hybrid analysis combines process data and I–O data to process-based hybrid analysis. EE must be considered over the whole life of the container housing Embodied Energy values. The EE values can be reduced with a careful consideration on the design of systems and selection of appropriate building material. The lack of sufficient databases in building LCA area is the most important issue of Turkey. More reliable and accurate estimates can be obtained with a wide range of databases in ANFIS modelling analyses.

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