ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

PhD THESIS

Erdi TOSUN

PREDICTION OF VARIOUS ENGINE-OUT PARAMETERS BY USE OF ARTIFICIAL INTELLIGENCE TECHNIQUES

DEPARTMENT OF MECHANICAL ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Doctor of Philosophy by the board of jury on 04/10/2018

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ABSTRACT

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Since experimental studies on internal combustion engines are both time consuming and costly, various modelling techniques can be used to predict experimental results. Artificial intelligence techniques are prominent among other techniques. These techniques can tackle complex, non-linear problems.

In this study, four different engine models were handled which intended to estimate various engine-out parameters. In Model 1, performance and emission parameters of a diesel engine operated with biodiesel-alcohol mixtures were estimated. In Model 2, performance and emission parameters of a diesel engine operated with diesel fuel with nanoparticle additives were estimated. In model 3, various operational parameters of a spark ignition engine operated with 95 RON (Research Octane Number) gasoline fuel were estimated. In model 4, vibration characteristic of a diesel engine operated with different diesel-biodiesel blends with HHO (hydroxyl gas) gas addition into intake manifold were estimated.

Regression analysis, artificial neural networks and adaptive neuro fuzzy inference system methods were used to make predictions. It was concluded that, regression analysis is not capable of predicting the parameters accurately. On the other hand, artificial neural networks and adaptive neuro fuzzy inference system made more accurate estimations.

Key Words: Internal combustion engine, Artificial neural networks, Adaptive neuro fuzzy inference system, Estimation

ÖZ

DOKTORA TEZİ

ÇEŞİTLİ MOTOR ÇIKIŞ PARAMETRELERİNİN YAPAY ZEKA TEKNİKLERİ KULLANIMI İLE TAHMİNİ

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İçten yanmalı motorlar da yapılan deneysel çalışmaların hem zaman kaybına sebep olması hem de maliyetinden dolayı, deneysel sonuçların tahmini için çeşitli modelleme teknikleri kullanılabilir. Yapay zekâ teknikleri diğer teknikler arasında öne çıkmaktadır. Bu teknikler karmaşık ve lineer olmayan problemlerin üstesinden gelebilirler.

Bu çalışmada, çeşitli motor çıkış parametrelerini tahmin etmeyi amaçlayan dört farklı motor modeli ele alınmıştır. Model 1'de, biyodizel-alkol karışımları ile çalıştırılan bir dizel motorunun performans ve emisyon parametreleri tahmin edilmiştir. Model 2'de dizel yakıtına eklenen nanopartiküller ile çalıştırılan bir dizel motorunun performans ve emisyon parametreleri tahmin edilmiştir. Model 3'de 95 oktan benzin ile çalıştırılan bir benzinli motorun çeşitli çalışma parametreleri tahmin edilmiştir. Model 4'de emme manifolduna HHO gazı verilen ve farklı biyodizel-dizel karışımları ile çalıştırılan bir dizel motorunun titreşim karakteristikleri tahmin edilmiştir.

Regresyon analizi, yapay sinir ağları, uyarlamalı sinirsel bulanık çıkarım sistemi yöntemleri tahmin yapmak için kullanılmıştır. Sonuç olarak, regresyon analizi doğru tahmin yapmada yetersizdir. Öte yandan, yapay sinir ağları ve uyarlamalı sinirsel bulanık çıkarım sistemi ile daha doğru tahminler yapılmıştır.

Anahtar Kelimeler: İçten yanmalı motorlar, Yapay sinir ağları, Uyarlamalı sinirsel bulanık çıkarım sistemi, Tahmin

EXTENDED ABSTRACT

Energy is a concept that is difficult to explain. It can commonly be expressed as ability to do work. Energy concerns a very broad area from social life of humans to country policies.

One of the areas where energy is most needed is the transportation sector. Internal combustion engines have an important place in this sector. These engines have shown considerable advances and progress since their invention and are still used extensively today. Fossil fuels are the fuels of living organisms that die and stay under the soil for millions of years in an oxygen-free environment. According to researches done, fossil fuels will be exhausted in the near future.

Fundamentally, internal combustion engines are the machines which convert the chemical energy in the fuel into mechanical energy. Researchers perform studies to be able to enhance the performance values of engines and decrease the combustion based harmful emissions. Especially, there are lots of experimental studies on this subject in Europa and United States. However, these conventional research techniques both time consuming and costly. Therefore, new approaches can be found to replace experimental studies. Computational Fluid Dynamics (CFD), Artificial Neural Networks (ANN) etc. can be given as examples for these alternatives. These approaches are frequently used in the automotive sector.

Artificial Intelligence (AI) systems can be used as a tool to handle complex and ill-defined problems. These systems can be trained. In other words, they can learn by use of past experiences. They will have the ability to predict and generalize when they have been taught with enough past experiences. Therefore, this means that they can overcome complex and ill-defined problems. Expert systems, artificial neural networks, genetic algorithms, fuzzy logic, adaptive neuro fuzzy inference systems etc. can be given as examples to artificial intelligence techniques.

Combustion process in an ICE is very complex and a mathematical relation that covers the engine is highly non-linear and they change with time. These all situations make very hard to obtain governing equations easily and solving them analytically. Besides that, there is also dependency with environmental conditions and engine load. Therefore, intelligent systems have widely been used in complex engineering problems. Software systems containing Artificial Intelligence have many advantages for controlling, modelling and prediction of the engineering problems. They are able to rapid learning capacity and they give relationship between input and output data. Studies on the engines such as performance enhancement, emission reduction, optimization, etc. require an intense experimental process. For instance, we might want to see how different alternative fuels will affect engine performance and emissions. Experimental processes will be repeated using different fuels on this way. This situation causes a serious waste of time and cost. Environmental pollution, human health and labour forces are also drawbacks of experimental studies. Therefore, the emission and performance characteristics of an engine can be determined with intelligence systems by avoiding complex and uncertain processes.

Artificial neural networks (ANN) mimic the biological neural networks of human nervous systems. The human brain is made up of many neural units called highly interconnected neurons. All human actions such as thinking, moving, remembering and so on take place by these connections. Artificial Neural Networks consist of neurons, basically 3 layers (input, secret, output) and these layers are formed by connecting to each other. These connections are called as weights. The signal coming from the outside world enters the system through the input layer. Input signal is transmitted to hidden layer and output layer via weights. Finally, system generates final output and gives to the external world. Artificial Neural Networks have lots of capabilities such as learning, classification, generalization, and optimization. They are often used in engineering applications.

ANFIS constructs fuzzy if-then rules with proper membership functions to generate input-output pairs. Just like in artificial neural networks, there is learning procedure from past experiences.

This learning is provided by the choice of if-then rules created with the selection of appropriate membership functions. ANFIS can be thought as a mix and integrated system of fuzzy systems and neural networks. They take the both advantages of neural networks and fuzzy systems. Automatic determination of system parameters is provided by artificial neural networks. In these systems, while creating system rules with fuzzy logic, the system is learned by using artificial neural network learning algorithm.

In this study, comparison of artificial intelligence modelling and experimental studies of various internal combustion engines for engine characteristic predictions were performed. In each model, various predictions were performed by various techniques and they are compared with experimental results.

In Model 1, performance and emission engine out-parameters were estimated by using LR and ANN. The inputs are engine speed, cetane number, heating value and density values of fuels. Engine torque, carbon monoxide were nitrogen oxides are predicted values. A data set was obtained by operating engine with different engine speeds and fuels. Some of these data were used for training purpose of prediction models. Remaining data were used to test the performance of the model. As seen from results, ANN gives more satisfactory results than linear regression for prediction of various engine-out parameters.

In Model 2, prediction of performance and emission parameters of a diesel engine operated by diesel fuel with nanoparticle additives was achieved by use of regression analysis, ANN and ANFIS. Inputs used for estimations were cetane number and engine speed. The predicted parameters were engine torque, carbon monoxide, carbon dioxide and nitrogen oxides. By using experimental results, the total data set was divided into two groups: training and testing as in previous Model 1. Total data set contain five blends. 85% of total data was used for training purpose. Remaining randomly selected 15% of data was used to test and evaluate the performance of the model. ANFIS gave satisfactory results.

In Model 3, prediction of operational parameters of a direct injection turbocharged spark ignition engine operated with gasoline was performed. In experimental studies, duration of injection, specific fuel consumption and exhaust gas temperature values were obtained with respect to engine load and speed. Load and engine speed (rpm) were used as input parameters for estimations. It was concluded that regression analysis was deficient for predictions. On the other hand, ANN and ANFIS approximations gave more satisfactory results for estimation of engine operational parameters.

In Model 4, prediction of engine vibration level of HHO gas generator installed compression ignition engine operated with different diesel-biodiesel blends were performed. The engine used for tests is naturally aspirated compression ignition engine. The engine is the same engine in Model 1 and 2. Engine spee, HHO flow rate , cetane number , lower heating value were selected as input to be able to estimate vibration level. Since regression analysis in the previous models did not give satisfactory results for estimation of engine-out parameters, only ANN and ANFIS modelling was applied to the data in Model 4. Acceptable predictions were conducted by use of both ANN and ANFIS methods. ANFIS gives more accurate results.

GENİŞLETİLMİŞ ÖZET

Enerji ifade edilmesi zor olan bir kavramdır. Ancak yaygın olarak iş yapabilme yeteneği olarak tanımlanabilir. Enerji, insanların gündelik yaşamından ülke politikalarına varıncaya kadar çok geniş bir alanı ciddi şekilde ilgilendirir.

Enerjinin en çok ihtiyaç duyulduğu alanlardan bir tanesi de ulaşım sektörüdür. İçten yanmalı motorlar bu sektörde önemli bir yere sahiptir. Bu motorlar icatlarından bu yana ciddi gelişmeler ve ilerlemeler göstermiş olup ve günümüzde halen yoğun şekilde kullanılmaya devam etmektedirler. Kullandıkları başlıca enerji kaynağı petrol kökenli fosil yakıtlardır. Fosil yakıtlar, canlı organizmaların ölüp, toprağın altında milyonlarca yıl oksijensiz ortamda kalmaları sonucu oluşan yakıtlardır ve yapılan araştırmalara göre yakın gelecekte tükenecek oldukları belirtilmektedir.

İçten yanmalı motorlar temel olarak yakıtın içerisindeki kimyasal enerjiyi, mekanik enerjiye dönüştüren makinelerdir. Araştırmacılar, bu makinelerin performans değerlerini yükseltebilmek ve yanma sonucu oluşan zararlı emisyonları azaltabilmek için çalışmalar yapmaktadırlar. Özellikle Amerika ve Avrupa’da bu konu ile ilgili yoğun deneysel araştırmalar yapılmaktadır. Ancak, bu geleneksel araştırma yöntemleri hem çok fazla zaman almakta hem de ciddi masraflar oluşturmaktadır. Bu yüzden, bu geleneksel deneysel araştırma yöntemleri yerine kullanılabilecek bazı yaklaşımlar bulunabilir. Bu tip yaklaşımlara örnek olarak; hesaplamalı akışkanlar dinamiği (HAD), yapay sinir ağları (YSA) vb. örnek olarak verilebilir. Bu yaklaşımlar özellikle otomotiv sektöründe sıklıkla kullanılmaktadırlar.

Yapay zekâ sistemleri karmaşık problemleri ele alıp, çözmede oldukça başarılı sonuç verirler. Bu sistemler eğitilebilir, bir başka ifade ile geçmiş tecrübeler kullanılarak herhangi bir olayı öğrenmesi sağlanabilir. Kendilerine yeteri kadar geçmiş tecrübeler tanıtıldığında, yani öğretildiğinde, tahmin etme ve genelleme yapabilme yeteneğine sahip olurlar. Bu da karmaşık problemlerin

üstesinden gelebilmeleri anlamına gelmektedir. Uzman sistemler, yapay sinir ağları, genetik algoritmalar, bulanık mantık, uyarlamalı sinirsel bulanık çıkarım sistemleri vb. yapay zeka tekniklerinden bazılarına örnek olarak gösterilebilir.

İçten yanmalı motorlardaki yanma olayı oldukça karmaşık bir süreçtir ve oldukça karmaşık denklemler ile ifade edilir. Dolasıyla, bu denklemlerin analitik çözümleri de bir hayli zor olmaktadır. Tüm bunların yanında çevresel etmenler ve motor yükü gibi parametreler de işi daha karmaşık hale getirmektedir. Bu yüzden, bu tarz mühendislik problemlerinin çözümlerinde akıllı sistemlerden faydalanılabilir. Yapay zeka tekniklerini kullanan yazılımlar ile bu problemlerin çözümüne yönelik modelleme, genelleme ve tahminler yapılabilir. Çünkü bu sistemlerin var olan girdi-çıktı veri setleri ile eğitilip kolayca öğrenmeleri sağlanabilir.

Motor üzerine yapılacak her türlü çalışma (performans iyileştirme, emisyon azaltma, optimizasyon vb.) yoğun deneysel süreç gerektirmektedir. Örneğin farklı alternatif yakıtların motor performans ve emisyon değerlerine nasıl etki edeceğini görmek isteyebiliriz. Bunun için farklı yakıtlar kullanılarak deneysel süreçler tekrarlanmalıdır. Bu durum hem ciddi bir zaman kaybına hem de masrafa yol açar. Motorlarda yapılan deneysel çalışmaların, çevre kirliliği ve insan sağlığına olumsuz etkiler, işgücü gibi dezavantajları vardır. Bu yüzden bu deneysel çalışmalar yerine akıllı sistemler (yapay zeka teknikleri) kullanılarak motor performans, emisyon ve yanması gibi karakteristikler kolayca belirlenebilir.

Yapay sinir ağları (YSA), insanların sinir sistemlerini oluşturan biyolojik sinir ağlarını taklit ederler. İnsan beyni oldukça karmaşık yapıdaki birbirleriyle bağlantılı nöron olarak adlandırılan birçok sinirsel birimden oluşur. Düşünme, hareket etme, hatırlama vb. tarzındaki tüm eylemler bu bağlantılar vasıtası ile gerçekleşir. Yapay sinir ağları nöronlardan oluşan, temelde 3 katman (girdi, gizli, çıktı) ve bu katmanların birbirleriyle bağlanması ile oluşturulur. Bu bağlantılar ağırlık olarak adlandırılır. Dış dünyadan gelen sinyal girdi katmanı yoluyla sisteme giriş yapar. Giren sinyal ağırlıklar yardımıyla gizli, oradan da yine ağırlıklar yardımıyla çıktı katmanına aktarılır. Ve sistem tek bir sinyal değeri üreterek dış dünyaya tekrar geri verir. Yapay sinir ağlarının öğrenme, sınıflandırma, genelleme, optimizasyon vb. gibi bir çok yeteneği vardır ve mühendislik uygulamalarında sıklıkla kullanılır.

Uyarlamalı sinirsel bulanık çıkarım sistemi (USBÇS) girdi-çıktı veri setleri kullanılarak ve bir dizi eğer-ise bulanık kurallar oluşturularak kurulur. Burada tıpkı yapay sinir ağlarında olduğu gibi geçmiş tecrübelerden öğrenme söz konusudur. Bu öğrenme uygun üyelik fonksiyonlarının seçimi ile oluşturulan eğer-ise kuralları ile sağlanır. Uyarlamalı sinirsel bulanık çıkarım sistemi, yapay sinir ağları ile bulanık sistemlerin avantajlarını bir araya getiren bütünleşik bir sistem olarak düşünülebilir. Sistem parametrelerinin otomatik olarak belirlenmesi yapay sinir ağları ile sağlanır. Bu sistemlerde, bulanık mantık ile sistem kuralları oluşturulurken, yapay sinir ağı öğrenme algoritması kullanılarak sistemin öğrenmesi sağlanır.

Bu çalışmada motor çıkış parametrelerini tahmin etmeye yönelik olarak çeşitli yöntemlerin kullanıldığı 4 farklı motor modeli ele alınmıştır. Her bir modelde farklı yöntemlerle tahminler yapılmış ve yapılan tahmin performansları hem birbirleriyle hem de deneysel sonuçlarla kıyaslanmıştır.

Model 1 olarak isimlendirilen ilk modelde bir dizel motoru kullanılmış, biyodizel-alkol karışımlarıyla çalıştırılan motorun performans ve emisyon çıktıları regresyon analizi ve YSA yöntemleri ile tahmin edilmeye çalışılmıştır. Bu parametreleri tahmin etmek için kullanılan girdiler motor devri, yakıtın setan sayısı, ısıl değeri ve yoğunluk değeridir. Tahmin edilmeye çalışılan motor parametreleri motor torku, karbon monoksit ve azot oksit emisyonlarıdır. Toplam veri seti iki gruba ayrılmış olup, bir kısmı eğitim için kullanılmış, geri kalan rastgele seçilen kısmı ise yöntemlerin tahmin performansını ölçmek için test verisi olarak kullanılmıştır. Tahmin sonuçları deneysel sonuçlar ile karşılaştırıldığında, YSA yönteminin, regresyon analizine göre daha iyi sonuç verdiği görülmüştür. Model 2 olarak isimlendirilen ikinci modelde bir dizel motoru kullanılmış olup, dizel yakıtına katkı olarak kullanılan çeşitli nanopartiküller ile çalıştırılan motorun performans ve emisyon çıktıları regresyon analizi, YSA ve USBÇS yöntemleri ile tahmin edilmeye çalışılmıştır. Bu parametreleri tahmin etmek için kullanılan girdiler motor devri ve yakıtın setan sayısıdır. Tahmin edilmeye çalışılan motor parametreleri motor torku, karbon monoksit, karbon dioksit ve azot oksit emisyonlarıdır. Eğitim veri seti ile sistem öğrenmesi sağlanmış, test veri seti ile de sistem tahmin performansları değerlendirilmiştir. Bu modelde uyarlamalı sinirsel bulanık çıkarım sisteminin tahmin performansının en iyi olduğu sonucuna varılmıştır. Model 3 olarak isimlendirilen üçüncü modelde direk enjeksiyonlu, turboşarjlı benzinli bir motor, yakıt olarak da 95 oktan benzin kullanılmıştır. Deneysel çalışmalar sonucunda motor yük ve devrine bağlı olarak püskürtme süresi, özgül yakıt tüketimi ve türbin girişindeki egzoz gaz sıcaklığı değerleri elde edilmiştir. Yapılan modellemeler ile motor devir ve yükünü girdi olarak kullanıp, elde edilen bu motor parametreleri tahmin edilmeye çalışılmıştır. Regresyon analizi, YSA ve USBÇS'nin kullanıldığı bu modellerde regresyon analizinin yetersiz olduğu, YSA ve USBÇS'nin daha iyi performans gösterdiği anlaşılmıştır. Model 4 olarak isimlendirilen dördüncü modelde Model 1 ve Model 2'deki dizel motoru kullanılmış olup, farklı biyodizellerin farklı oranlarda dizel yakıtı ile karıştırılıp, emme manifoldundan farklı debilerde hidroksil gazının verildiği ve motorun farklı yakıt karışımları ve verilen hidroksil gazı miktarına göre değişen titreşim karakteristikleri incelenmiştir. Motor devri, hidroksil gaz debisi, setan sayısı ve ısıl değerin girdi parametresi olarak kullanılmış ve motorun titreşim karakteristiği tahmin edilmeye çalışılmıştır. Bir önceki modellerde regresyon analizinin yetersiz tahmin yeteneğine sahip olduğu görüldüğünden burada, YSA ve USBÇS kullanılmıştır. USBÇS'nin tahmin yeteneğinin daha iyi olduğu anlaşılmıştır.

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ABBREVIATIONS

AFR	:	Air-Fuel Ratio
AI	:	Artificial Intelligence
ANFIS	:	Adaptive Neuro Fuzzy Inference System
ANN	:	Artificial Neural Network
BMEP	:	Brake Mean Effective Pressure
BNN	:	Biological Neural Network
BPA	:	Back-Propagation Algorithm
BSEC	:	Brake Specific Energy Consumption
BSFC	:	Brake Specific Fuel Consumption
BTE	:	Brake Thermal Efficiency
CI	:	Compression Ignition
CL	:	Classical Logic
CN	:	Cetane Number
CNG	:	Compressed Natural Gas
CO	:	Carbon Monoxide
CO_2	:	Carbon Dioxide
DOI	:	Duration of Injection
EGT	:	Exhaust Gas Temperature
FES	:	Fuzzy Expert System
FIS	:	Fuzzy Inference System
FL	:	Fuzzy Logic
GA	:	Genetic Algorithm
HC	:	Hydrocarbon
HHO	:	Hydroxyl Gas
ICE	:	Internal Combustion Engine
IT	:	Injection Timing

LHV	: Lower Heating Value
LMA	: Levenberg-Marquardt Algorithm
LPG	: Liquefied Petroleum Gas
LR	: Linear Regression
MAPE	: Mean Absolute Percentage Error
MEP	: Mean Effective Pressure
MF	: Membership Function
NLR	: Non-linear Regression
NO_x	: Nitrogen Oxides
PM	: Particulate Matter
RBF	: Radial Basis Function
RMSE	: Root Mean Square Error
SCG	: Scaled Conjugate Gradient
SFC	: Specific Fuel Consumption
SI	: Spark Ignition
SVM	: Support Vector Machine

1. INTRODUCTION

Although it is very hard to define the term of energy, it can commonly be described as ability to work. There are various forms of energy as electric, thermal, solar, mechanical, chemical, nuclear, wind etc.

Energy plays important role in human life and country policies and it is also very crucial for economic and social development (Bilgili et al., 2015). It is very essential for human welfare which includes basic necessities, health care, employment, sustainability etc. (Shakeel et al., 2016). Besides that, increment of human population cause to occur global energy problems in the world. Energy consumption of countries is rapidly increasing with parallel to world growth in human population, dependently. Coal, petroleum and natural gas are the primary energy sources of the world. Investigations showed that these conventional sources have limited reserves. Therefore, scientists are trying to find new renewable alternative energy sources in order to meet energy demand (Demirbas, 2007).

Remarkable amount of energy are consumed in transportation sector worldwide. Transportation sector has significant and basic features of economic activities and it is one of the most foremost energy consumers of petroleum based fuels. This sector is also responsible for environmental problems (Zarifi et al., 2013). Energy use in transportation sector can be divided into two groups. One is road transportation sources to environmental problems and the other one is subjected to energy supply for this sector of countries (Zhang, 2011). There is a direct and powerful relation in between energy consumption and level of development. Transportation energy consumption rate constitute between 20 and 25% of total energy consumption in developed countries (Rodrigue et al., 2013). United States, for instance, consumes huge amount of energy. Kialashaki and Reisel (2013) stated that, the transportation sector is the second biggest energy consumer after electric power sector. Sectoral energy distribution in Turkey can be seen from Figure 1.1. As seen from the figure that, transportation part of total energy consumption is notable.

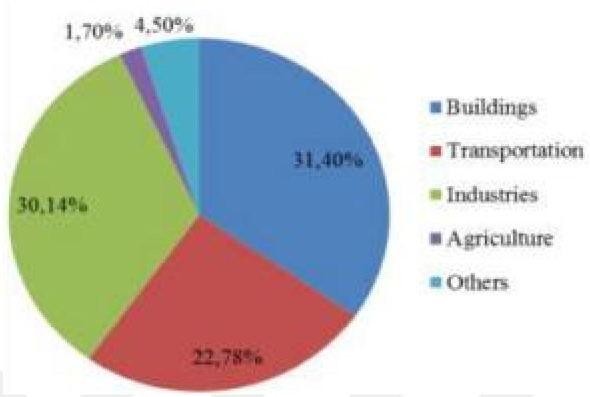


Figure 1.1. Sectoral energy distribution in Turkey (Cetin, 2017)

Progresses on industry cause to high demand on fossil fuels. The invention and commercialization of internal combustion engines (ICE) enable people to move efficiently at beginning of twentieth century (Rodrigue et al., 2013). ICEs are the heart of transportation sector.

A typical ICE converts chemical energy taken from fuel into mechanical energy. Chemical energy is converted to heat energy by oxidizing fuel with oxygen in the air, then; this heat energy is converted to useful mechanical energy with use of a kind of mechanism. Useful energy can be taken on a shaft. The term “internal” states that combustion occurs in a closed volume.

In 17th and 18th centuries, most of the ICEs are atmospheric. They were very big and had a single piston cylinder configuration. In these early engines, exhaust gases are being allowed to cool just after combustion of fuel. Cooling of products will create a vacuum effect in cylinder and pressure differential across piston (vacuum versus atmospheric pressure across piston) (Pulkrabek, 2004). These engines were not very efficient. With parallel to research and development studies on ICE, much more efficient engines are being produced nowadays.

In today's world, two types of ICEs are very widespread; gasoline and diesel engine. They have some differences in the base of working principle. Gasoline engines are also called as spark ignition (SI) engines. In SI engines fuel is ignited by a spark. On the other hand, diesel engines are also called as compression ignition engines (CI). In a CI engine, increase in temperature and pressure during compression stroke is adequate for ignition of fuel by itself (Stone, 1992). Combustion sources of SI and CI engines in power stroke can be seen from Figure 1.2.

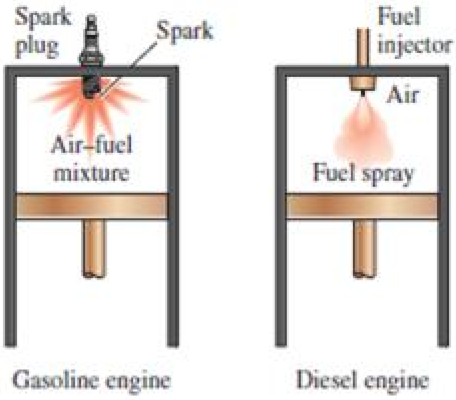


Figure 1.2. Power strokes in SI and CI engines (Çengel and Boles, 2015)

Besides being power sources of vehicles, ICEs have broad application areas such as garden equipment, stationary electrical power generation, ships, locomotives etc. (Caton, 2016).

Performance enhancement and emission reduction studies are very important issues for scientists. In course of time, there were great advances in experimentation and research studies in United States and Europa in the latter half of the 1800s (Pulkrabek, 2004). Especially, in the area of power, propulsion and energy, with support of developers and manufacturers of them, ICEs play a dominant role. Since market competitiveness, air pollution and fuel cost issues have become significant, there were considerable growth in engine research and development studies (Heywood, 1988).

Conventional engine research studies are both difficult and costly to meet the emissions limits forced by legislations. Therefore, conventional methods have been replaced by cost effective approaches such as artificial neural networks (ANN), computational fluid dynamics (CFD) and kinetic modelling. Among these techniques, ANN is remarkable. It has progressively been used as a modelling tool in automotive area in order to make quick predictions for miscellaneous engine-out parameters when new strategies in engine operating conditions are being tested. On the other hand, disadvantage of CFD and chemical kinetic modelling techniques is requirement of too much computing resources for accurate results (Ismail et al., 2012).

Artificial Intelligence (AI) systems can be used as a tool to handle complex and ill-defined problems. These systems are able to learning capacity by examples. Non-linear problems can easily be tackled with them and they are capable of prediction and generalization capacity after once trained. Expert systems, artificial neural networks, genetic algorithms, fuzzy logic or combination of them as adaptive neuro fuzzy inference system (ANFIS) can be given as examples for AI systems (Rai et al., 2012).

Combustion process in an ICE is very complex and a mathematical relation that covers the engine is highly non-linear and they change with time. Besides that, there is also dependency with environmental conditions and engine load. These all situations make very hard to obtain governing equations easily and solving them analytically (Behnam et al., 2012). Therefore, intelligent systems have widely been used in engineering problems. Software systems containing AI have many advantages for controlling and modelling of the engineering problems. They are able to rapid learning capacity and they give relationship between input and output data (Isin and Uzunsoy, 2013). On the other hand, engine manufacturers perform engine test to determine performance and emission characteristics of an engine. Engines are also being tested with different engine modifications and operated with alternative fuels in order to see effects on engine performance. These all processes are both expensive and time consuming. Environmental pollution, human health and labour forces are also drawbacks of experimental studies. Therefore, the emission and performance characteristics of an engine can be determined with intelligence systems by avoiding complex and uncertain processes (Tasdemir et al., 2011).

Experiment based approaches as ANN and fuzzy logic are being used with respect to mathematical models, alternatively (Berber et al., 2011). ANNs are inspired from biological neural networks (BNN). In BNN, there is flow of information from synapses through axon. Information goes through from a neuron to the other and so on (Najafi et al., 2007). The main idea of an ANN is connection strength and learning concept. Basically, ANNs adjust the connection strengths which are assigned randomly at the beginning of process. The network must be supplied with sufficient input data for training purpose of system. Typical network consist of three main layers: input, hidden (one or more) and output (Taghavifar et al., 2016). A FIS system uses a set of if-then rules and it can model qualitative sides of human knowledge and reasoning processes without needing to precise quantitative analyses. But there is no standard procedure in order to transform human knowledge or experience into the rule base and also no effective way for adjusting membership functions. ANFIS can construct set of fuzzy if-then rules with suitable membership functions to constitute the stipulated input-output pairs (Jang, 1993). ANFIS combines fuzzy logic and artificial neural networks. It generates a fuzzy inference system (FIS). Membership function of FIS is arranged using either a backpropagation algorithm alone or with least square method which let the fuzzy system learn from data. Relationship between input and output is identified by self-learning procedure. ANFIS models are able to solve problems by utilizing training data (Yang and Entchev, 2014).

In this study, comparison of artificial intelligence modelling and experimental studies of various internal combustion engines for engine characteristic predictions were performed. Four different engine models were handled which intended to estimate various engine-out parameters. In Model 1, performance and emission parameters of a diesel engine operated with biodiesel-alcohol mixtures were estimated. In Model 2, performance and emission parameters of a diesel engine operated with diesel fuel with nanoparticle additives were estimated. In model 3, various operational parameters of a spark ignition engine operated with 95 RON gasoline fuel were estimated. In model 4, vibration characteristic of a diesel engine operated with different diesel-biodiesel blends with HHO gas addition into intake manifold were estimated.

2. PRELIMINARY WORK

Since AI techniques have notable advantages, these techniques have widely been used in many engineering areas recently. In literature, many researchers used various AI models for prediction of engine-out parameters.

2.1. Artificial Neural Network Literature Review

Lucas et al. (2001) modelled diesel particulate emissions with neural networks. They tested eight different fuels in a diesel engine and investigated effects of fuel composition on particulate emission with use of neural networks. Yuanwang et al. (2002) investigated the effect of cetane number on exhaust emissions of the engine with neural network. They used back-propagation (BP) neural network algorithm. Total cetane number, base cetane number and cetane improver, total cetane number and nitrogen content in the diesel fuel were inputs and hydrocarbon (HC), carbon monoxide (CO), particulate matter (PM) and nitrogen oxide (NO_x) emissions were outputs for prediction. Optimal number of hidden layers, hidden layer neuron numbers and activation function were determined with suitable weight and bias values in model. Ismail et al. (2012) studied an ANN model for a light-duty diesel engine fuelled with blends of various biodiesel and diesel fuels. They used ANN in order to predict engine-out responses as carbon monoxide, carbon dioxide, nitrogen monoxide, unburned hydrocarbon, maximum pressure, location of maximum pressure (crank angle based), maximum heat release rate, location of maximum heat release rate (crank angle based), cumulative heat release rate. For prediction, engine speed, torque, mass flow rate of fuel and biodiesel fuel types and blends were used as input. The model was able to predict seven out of nine engine-out responses accurately. Yusaf et al. (2011) studied the effect of using crude palm oil-ordinary diesel blends as fuel on the performance of compression ignition engine. Different mixture rates of fuel were used. Experiments were conducted between 1000-3000 engine speeds. ANN model was constructed to predict power, brake specific fuel consumption, carbon monoxide, nitrogen oxides and exhaust gas temperature. They showed that the advantages of such a model usage are being fast, accurate and reliable. Çay et al. (2013) studied an ANN model to estimate brake specific fuel consumption (BSFC), exhaust emissions; CO and UHC, air-fuel ratio (AFR) of a SI engine fuelled with methanol and gasoline. They divided total data into two groups; training and testing and they decided BP algorithm was the best choice to use for training the network. ANN models predicted the outputs, BSFC, CO, UHC and AFR, with correlation coefficients of 0.998621, 0.977654, 0.998382 and 0.996075 for testing data, respectively. Jahirul et al. (2013) applied an ANN model for estimating performance of a dual fuelled internal combustion engine. Levenberg-Marquardt (LM) and scaled conjugate gradient (SCG) algorithms were used as learning algorithms. One hidden layer with sigmoid transfer function was selected. Inputs were engine load, engine speed and diesel-natural gas ratio and outputs for prediction were engine thermal efficiency, break specific fuel consumption, exhaust temperature and air-fuel ratio. Arcaklioglu and Çelikten (2005) have performed performance and emission engine experiments with different injection pressure, engine speed and throttle positions. The investigated parameters were engine torque, power, brake mean effective pressure, specific fuel consumption, fuel flow, and exhaust emissions as SO_2, CO_2, NO_x and smoke level. Injection pressure, engine speed, and throttle position were used as inputs where engine performance and emission parameters were used as outputs. R^2 values are 0.9999 and 0.999 for training and testing data, respectively. ANN results with good correlation and small errors were considered as acceptable for estimation. Wu and Liu (2012) predicted car fuel consumption using a radial basis function (RBF) neural network. For training purpose, make of car, engine style, weight of car, vehicle type and transmission system type were used as input. Fuel consumption of car was forecasted parameter. The results show that ANN was able to predict car fuel consumption effectively. Cirak and Demirtas (2014) applied an ANN model to biodiesel fuelled engine for prediction of engine torque. Biodiesel used in tests were canola and soybean. Results of experiments were divided into training and testing sections. Input layer consisted of engine speed, biofuel mixture, coolant temperature and exhaust gas temperature in order to predict torque. The results showed that ANN was able to predict engine torque with good accuracy. The correlation between experimental and predicted results was 0.98. Parlak et al. (2006) investigated that prediction capability of ANN model for SFC and exhaust temperature of diesel engine. Back propagation learning algorithm was used in model. Three parameters; engine speed, mean effective pressure (MEP) and injection timing; two parameters: specific fuel consumption and exhaust temperature were used as input and output neurons, respectively. Predictions were performed with mean absolute relative error less than 2%. Kiani et al. (2010) studied that estimation of performance and emission characteristics of an SI engine operated with gasoline-ethanol mixtures. Engine tests performed with different percentages (0, 5, 10, 15 and 20%) of ethanol at different load and speeds. Blends, speed and load of engine were utilized as input for prediction of power, torque and exhaust emissions as CO, CO_2, NO_x and HC. Totally, ANN gave fast and accurate responses for predictions. Muralidharan and Vasudevan (2015) applied ANN for prediction of performance, emission and combustion characteristics of engine which have variable compression ratio engine operated with waste cooking oil biodiesel. Three different ANN architectures with feed forward BP algorithm were generated. For training purpose, compression ratio, blend percentage and load were used as input layer neurons. The predicted performance parameters were brake thermal efficiency, specific fuel consumption, brake power, indicated mean effective pressure, mechanical efficiency and exhaust gas temperature. The predicted emission parameters were CO_2, CO, HC and NO_x. For combustion parameters prediction, crank angle was also used as input neuron besides compression ratio, blend percentage and load. The predicted combustion parameters were combustion pressure, heat release rate, ignition delay, combustion duration and mass fraction burnt. Ozener et al. (2013) studied ANN model in order to estimate engine performance and emission parameters of an internal combustion engine. They predicted torque, power, brake specific fuel consumption and emissions; CO_2, CO, NO_x, HC, and filter smoke number. Experimental data were collected from 4-stroke, 4 cylinder, and turbocharged diesel engine. They finally concluded that ANN model was satisfactory for estimation of engine-out parameters. Kannan et al. (2013) aimed to estimate effect of injection pressure and timing on performance, emission and combustion characteristics of a diesel engine. In this respect, an ANN model was developed. BP algorithm was used in structure. Different networks were tested and it was concluded that two hidden layer and 11 neurons for hidden layer gave good correlation for predictions. They suggested ANN to use for prediction of engine parameters which were performed with various operating conditions in order to avoid time consuming and complex experiments. Gölcü et al. (2005) modelled an ANN based on variable valve-timing in an engine. They intended to determine influences of timing of intake valve on engine performance and fuel economy. They divided total experimental data into train and test sections. In input layer, intake valve timing and engine speed were used. Torque and fuel consumption were the predicted variables by using inputs. In testing period root mean square error (RMSE), fraction of variance (R^2) and mean absolute percentage error (MAPE) values were 0.9017%, 0.9920% and 7.2613% and 0.2860%, 0.9299% and 7.5448% with respect to torque and fuel consumption, respectively. They suggested ANN as suitable method for performance predictions of SI engine. Yusaf et al. (2010) studied ANN model that predicted some engine performance and emission parameters. Experimental data were collected from a diesel engine operated with diesel-compressed natural gas (CNG) mixtures. BP algorithm was decided as best choice for learning of ANN. Engine speed and percentage of CNG were used as input. Various activation functions and neuron numbers for hidden layer were tried and the structure which gave minimum error for estimations was selected. They suggested ANN for accurate and simple simulation of engine tests. Shanmugam et al. (2011) investigated prediction of performance and emission of a hybrid fuelled diesel engine. The engine used is single cylinder and four strokes. Tests were performed at different loads. 70% of data was used to train, remaining 30% data was used to test network. BP algorithm was used. Correlation coefficients of predictions were between 0.975-0.999 and it means that ANN was very confident method for predictions. Sayin et al. (2007) studied ANN modelling of a gasoline engine to estimate BSFC, brake thermal efficiency, exhaust gas temperature and exhaust emissions. The engine was four cylinders, 4-strokes and it was fuelled with gasoline fuel with different octane numbers, engine speeds and torque values. The total data set were divided into two sections; training and testing. Correlation coefficient values were obtained between 0.983-0.996. On the other hand, relative errors were obtained between 1.41-6.66%. Kapusuz et al. (2015) used different alcohol and unleaded gasoline blends for performance tests on a SI engine. An ANN model was generated for prediction of torque, power and BSFC. Engine speed, ethanol and methanol percentages were used as input neurons in structure. There were 70 data sets and 60/70 of total data was used for training purpose and 10/70 was used for testing the performance of ANN. LM algorithm was selected as training algorithm. Weight and bias values were updated with the gradient descent with momentum back propagation algorithm. Transfer function was decided with trial and error method. Totally ANN gave satisfactory results for predictions. Atik et al. (2013) modelled ANN of a SI engine for estimation of engine performance and emissions. ANN model was coded in Visual Basic programming language. Inputs were H_2% rate, engine speed and excess air ratio for estimations. The correlation coefficients were 0.9840, 0.9252, 0.8650 and 0.9605 for power, specific fuel consumption, engine torque, and exhaust temperature, respectively.

2.2. Adaptive Neuro Fuzzy Inference System Literature Review

Al-Hinti et al. (2009) used neuro-fuzzy approach to see influences of boost pressure on efficiency, BMEP and BSFC of a single cylinder CI engine. Experimental data were used to estimate performance characteristics as input. Match between experimental results and ANFIS predictions were acceptable. Percentage errors for estimated efficiency, BMEP and BSFC were 1.64%, 0.15% and 2.43%, respectively. Taghavifar et al. (2015) constructed an ANFIS model for accumulated heat from hydrogen-fuelled engine. Crank angle, equivalence ratio, penetration and mass fraction of H_2 were used for prediction. They stated that trimf membership function for each three inputs and linear for output gave best performance. RMSE and R^2 values were 0.011527 and 0.999 with these functions, respectively. Hosoz et al. (2013) studied that application of an ANFIS in order to model performance and emission of a CI engine operated with various fuels. The tests for modelling were performed with a direct injected and single cylinder CI engine with diesel and diesel-biodiesel blends by varying engine speed and load under steady state conditions. Predicted variables with use of ANFIS were power, BSFC, brake thermal efficiency, exhaust gas temperature, HC, CO and NO. 0.940-1.000 range was obtained for correlation coefficients between experimental and prediction results. Relative errors were between 1.40-27.40% for emission and performance parameters predictions. Ozkan et al. (2015) estimated performance and emission of an engine with use of ANFIS. Engine was operated with alcohol-diesel mixtures. Experimental results were obtained from direct-injection, single cylinder, four-stroke engine with various spraying pressures. All data were divided into training and testing section. Torque, specific fuel consumption, air consumption, efficiency and lambda were predicted. Correlation coefficients of predicted outputs were close to 1 and this means that there was good match between experiment and ANFIS model results. Rai et al. (2015) estimated performance and emission of dual fuelled CI engines by using ANFIS. Input parameters were load (%), liquefied petroleum gas (LPG) (%) and injection timing

(IT). These all inputs were used to estimate brake specific energy consumption (BSEC), brake thermal efficiency (BTE), exhaust gas temperature (EGT) and smoke. To be able to optimize ANFIS results genetic algorithm (GA) was used. Prediction accuracy was increased with use of GA except for smoke. Najafi et al. (2016) used support vector machines (SVM) and ANFIS for estimation of performance and emission parameters. An SI engine was operated with ethanol-gasoline mixtures of 0, 5, 10, 15 and 20 percentages by volume. In ANFIS modelling, Gaussian curve membership function (gaussmf) and 200 epochs were selected as the optimum parameters for the training purpose. Correlation coefficient and accuracy values were in between 0.760-1 and 79.270-98.810 % for ANFIS results, respectively. They concluded that ANFIS can predict more accurately than SVM. Roy et al. (2015) studied ANFIS model for estimation of performance and emission parameters of CI engine operated with CNG dual-fuel operation. They showed the effects of load, fuel injection pressure and CNG energy share on prediction of BSFC, BTE, NO_x, PM and HC. 0.998875-0.999989 correlation coefficient range was obtained between experimental and model results. On the other hand, MAPE values varied between 0.08-1.84%. Finally they suggested their models to use. For various experimental conditions, this predictive model can be used. Gopalakrishnan et al. (2011) studied modelling approach to predict emissions of biodiesel fuelled transit buses. They measured NO_x, HC, CO, CO_2 and PM with portable emission measurement system and they used two approach called as ANFIS and the Dynamic Evolving Neuro-Fuzzy Inference System (DENFIS). Totally, ANFIS gave better performance than DENFIS and the best performance accuracies were obtained for NO_x and CO_2 for both ANFIS and DENFIS.

3. MATERIAL AND METHOD

The abilities of computers to perform miscellaneous tasks have rapidly been advancing with parallel to progresses in computer technology since their invention. Artificial Intelligence (AI) can be defined as machine ability to perform some functions that characterize human thinking. AI systems aim to design intelligent machine systems that have intelligence like in human behaviour as reasoning, learning etc. (Mellit and Kalogirou, 2008). Nowadays, AI techniques have widely been used in different areas which include medical, automation, games etc. (Ali et al., 2015). Figure 3.1 summarizes different disciplines on which AI based on (Rupnawar et al., 2016).

AI focuses on working principle of human brain and creates adaptive learning systems which can edit the behaviour of the system on the basis of information supplied (Shambhu and Rinku, 2015).

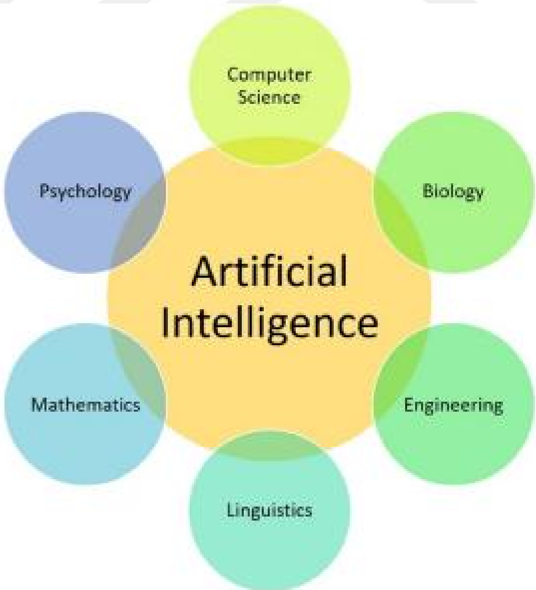


Figure 3.1. Different disciplines AI used

There are various AI techniques used by researchers, namely, artificial neural networks, fuzzy systems, genetic algorithms, ant colony optimization, particle swarm optimization, artificial immune systems etc. (Ansari and Bakar, 2014).

3.1. Artificial Neural Networks (ANNs)

It will exactly be more beneficial to explain biological neural networks (BNN) or human nervous system before passing to ANNs.

The basic component of the human nervous system is called as neuron. Neurons are excitable units which communicate with other neurons. Human brain consists of a series of interconnected neurons which help us to perform some abilities such as think, remember etc. Each neuron can connect with other neurons up to 200.000 (Amayreh and Saka, 2005).

A typical neuron consists of four basic elements called as dendrites, soma, axon, and synapses. They get input information from the outside and process them to perform generally nonlinear operation on result as output signal (Tosun and Çalık, 2016). A biological neuron with its fundamental components can be shown as in Figure 3.2.

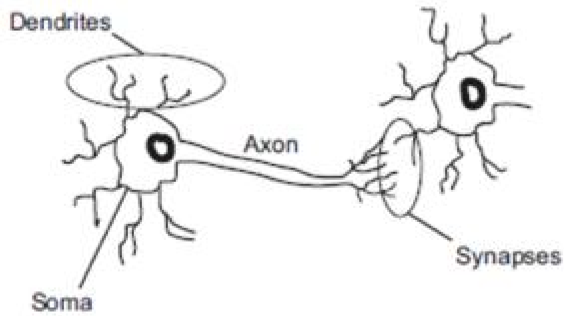


Figure 3.2. A typical biological neuron (Tosun and Çalık, 2016)

Axons are transmission lines and dendrites are receptive zones of the system. Synapses which are also called as nerve endings are fundamental units that make connections between neurons (Haykin, 2009).

A human nervous system can be demonstrated as 3-stage system which was showed in Figure 3.3 (Haykin, 2009).

Figure 3.3. Nervous system block diagram

In this block diagram brain is represented by neural net. It continually gets signals and senses this information. Finally, it makes suitable decisions. The continuous arrow (from left to right) represents transmitting information in a forward way. The dashed arrows (from right to left) show the feedback of the system. Stimuli from human body or external world are converted to electrical impulses by receptors and then information is transmitted to the neural net. The effectors convert electrical signals into certain and discernible outputs called as responses (Haykin, 2009).

Origin of ANN concept comes from BNNs. BNNs consist of high number of interconnected units called as neurons. Human brain can be thought as complex, non-linear and parallel supercomputer. An ANN structure contains lots of neurons which situated in various interconnected layers by links of numbers called as weights (Boruah and Thakur, 2016).

Studies on human brain have been continuing for years. ANN studies which are inspired from human brain accelerated with developments in modern electronics. First ANN model was constructed by an American neurophysiologist Warren Sturgis McCulloch and logician Walter Pitts in 1943. They modelled a simple neural network with an electric circuit by inspiring from calculation ability of human brain (Elmas, 2016).

An artificially modelled neuron can be seen from Figure 3.4.

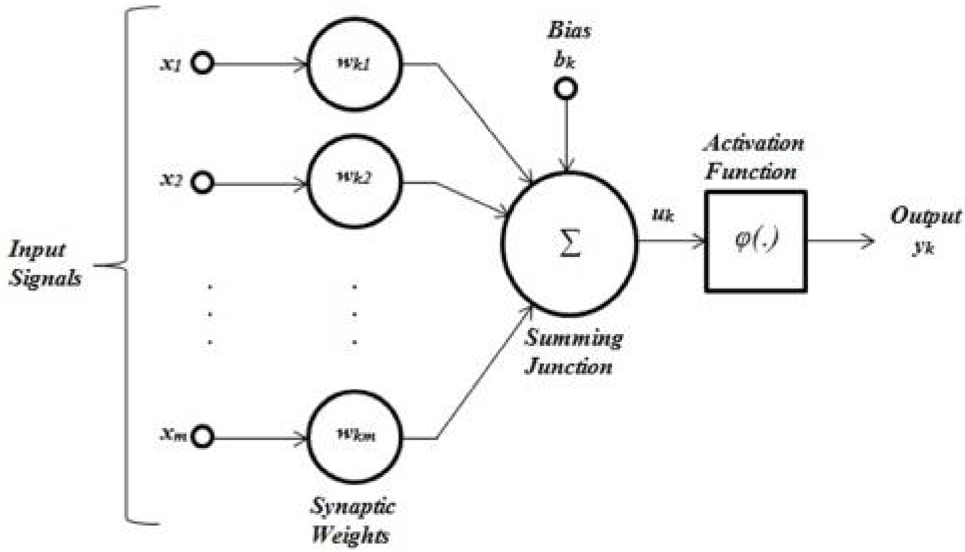


Figure 3.4. Model of a neuron (Haykin, 2009)

As biological neurons, artificial neurons have fundamental units. Every artificial neuron has 5 basic units (Öztemel, 2012):

- *Inputs:* Information coming from external world. It can also come from another neuron.
- *Weights:* The importance and effect of information coming to neuron can be determined by weights. Numerical values of weights (big or small) do not define the importance of them. For example, a weight can be zero and it can be very important for the network.
- *Summing function:* This function calculates the net input of a neuron. Different functions can be used for this purpose. Weighted summation is the most popular method. In this method, every input value is multiplied by its own weight and net input can be found.

- *Activation function:* This function calculates output value by processing net input coming to neuron. As in summing function, there are various activation functions. Table 3.1 summarizes various activation functions (Öztemel, 2012). Activation function gives a curvilinear relationship between inputs and outputs. Selection of suitable activation function is very important. It directly affects the performance of network (Eryilmaz et al., 2016).
- *Outputs:* It is the output value which is determined by activation function. Produced output is sent to the external world or to another neuron.

Table 3.1. Various activation functions

Linear Function	$F(NET) = NET$
Step Function	$F(NET) = \begin{cases} 1 \; if \; NET > threshold \; value \\ 0 \; if \; NET \leq threshold \; value \end{cases}$
Sine Function	$F(NET) = Sin(NET)$
Threshold Value Function	$F(NET) = \begin{cases} 0 & if & NET \leq 0 \\ NET & if & 0 < NET < 1 \\ 1 & if & NET \geq 1 \end{cases}$
Hyperbolic Tangent Function	$F(NET) = (e^{NET} + e^{-NET})/(e^{NET} - e^{-NET})$
Sigmoid Function	$F(NET) = \frac{1}{1 + e^{-NET}}$

Figure 3.5 demonstrates the graphical representations of some of the transfer functions commonly used.

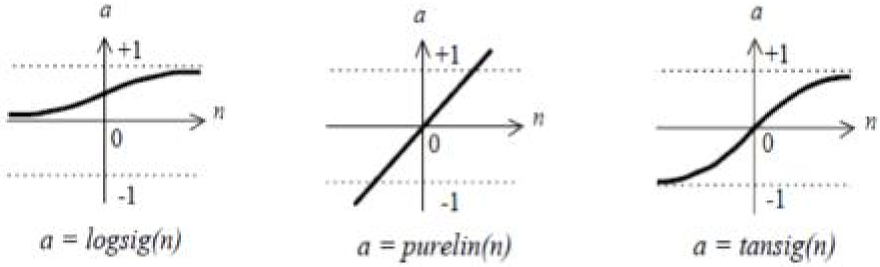


Figure 3.5. Graphical representations of some transfer functions (Chandak et al., 2014)

3.1.1. Mathematical Representation of an Artificial Neuron

Mathematically, a neuron k (Figure 3.4) can be represented by equations below:

$$u_k = \sum_{j=1}^{m} w_{kj}\, x_j \tag{3.1}$$

$$y_k = \varphi(u_k + b_k) \tag{3.2}$$

where $x_1, x_2, \dots, x_m$ are input signals; $w_{k1}, w_{k2}, \dots, w_{km}$ are synaptic weights of neuron k; u_k is linear combiner output; $\varphi(.)$ is activation function; y_k is output signal of neuron; b_k is externally applied bias.

3.1.2. Main Structure of an ANN

Artificial neurons form ANNs by coming together. In network, artificial neurons appear in some definite parallel layers. These are input, hidden and output layers (Öztemel, 2012):

- *Input layer:* This layer responsible to conduct the data coming from external world to the hidden layer.

- *Hidden layer:* In this layer, data coming from input layer is processed and it is sent to output layer. A network may have more than one hidden layer.
- *Output layer:* Output layer processes the data coming from hidden layer and generates an output.

An example of an ANN with its fundamental interconnected parallel layers can be seen from Figure 3.6.

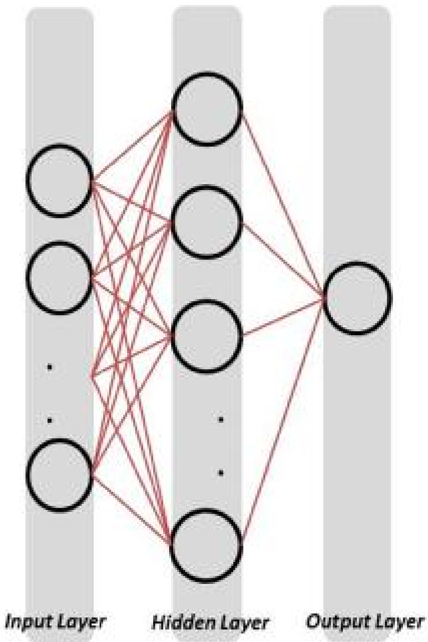


Figure 3.6. A typical ANN structure

3.1.3. Abilities and Applications of Neural Networks

The beneficial properties and capabilities of neural networks can be sorted as shown below (Haykin, 2009):

- *Nonlinearity:* A neural network can consist of interconnected nonlinear neurons. It is very important ability in order to handle nonlinear physical problem.
- *Input-output mapping:* In network, learning term states arrangement of synaptic weights by supplying a set of training examples to the system. These given data to the system for training purpose have definite input signals and corresponding outputs (response). Synaptic weights are arranged to minimize difference between desired output and network output which is generated by input signal with suitable statistical criteria. Network is trained many times with examples in the set until network approaches steady case where no further big changes in weight values. Network constructs input-output mapping and it learns by examples for problem handled.
- *Adaptivity:* Neural networks are able to adapt their weights for changing in the environment. For example, when minor changes in environmental conditions occur, network can be retrained. It is very useful property of neural networks in order to make adaptive pattern classification, adaptive signal processing or adaptive control etc.

Learning, classification, generalization, specification and optimization tasks can be achieved by using ANNs as functional properties of brain. ANNs can generate its own experiences and they can make decisions on similar subjects (Öztemel, 2012).

3.1.4. Learning Strategies in ANN Systems

Learning can be defined as modifying the weight and bias values between layers of the network. There are various learning strategies in ANN systems. System which will learn and learning algorithm used changes with respect to these learning strategies. Generally, three different learning strategies are used (Öztemel, 2012):

- *Supervised learning:* In this type learning, learning rule is supplied by a set of examples $(\{p_1, t_1\}, \{p_1, t_1\}, \dots, \{p_q, t_q\})$. Here, p_q and t_q are input and corresponding target, respectively. The network outputs are compared with target values when inputs are provided to the network. Then, the learning rule is used to modify the weight and bias values of the network to obtain more close values of network outputs to target values (Demuth and Beale, 2002).
- *Unsupervised learning:* The weights and biases are modified by using inputs only. There are no target values and most of these algorithms used to perform clustering operations. Categorization of inputs into finite numbers of classes is achieved. It is beneficial to use applications such as vector quantization (Demuth and Beale, 2002).
- *Reinforcement learning:* In this strategy, a supervisor helps to the system which will learn. A supervisor does not show each input and corresponding output value to the system. Inputs are supplied to the system and it generates outputs with respect to given input and a signal is generated. This signal demonstrates whether result is correct or not. Linear vector quantization (LQV) can be given as example for this learning (Öztemel, 2012).

Table 3.2 demonstrates a comprehensive organization of learning methods commonly used.

Table 3.2. Summary of learning methods (Yegnanarayana, 2005)

Categories of learning
Supervised, reinforcement and unsupervised
Off-line and on-line
Deterministic, stochastic and fuzzy
Discrete and continuous
Criteria for learning
Hebbian learning
Basic Hebbian learning
Differential Hebbian learning
Stochastic versions
Competitive learning - learning without a teacher
Linear competitive learning
Differential competitive learning
Linear differential competitive learning
Stochastic versions
Error correction learning - learning with a teacher
Perceptron learning
Delta learning
LMS learning
Reinforcement learning - learning with a critic
Fixed credit assignment
Probabilistic credit assignment
Temporal credit assignment
Stochastic learning
In multilayer perceptron
In Boltzmann machine
Other learning methods
Sparse coding
Min-max learning
Principal component learning
Drive-reinforcement learning

3.1.5. Backpropagation Algorithm

The backpropagation algorithm (BPA) is very popular learning algorithm among other supervised learning strategies and it can be applied wide range of practical problems. In this type of learning algorithm, input signals moves in a forward way and an error signal which is the difference between target and actual output value is calculated. Finally, the error is back propagated until error is minimized, iteratively (Turkson et al., 2016).

Turkson et al. (2016) gave formulations and logic behind the BPA as shown below:

Assume a feedforward network which have an output and bias, y_i^k, b_i^k, in i^{th} neuron of layer k. The relation between input and output of the network can be shown as:

$$y_i^k = \varphi\left[\sum_{j=1}^{k-1} w_{ij}^{(k-1)} y_j^{(k-1)} + b_i^k\right] \tag{3.3}$$

Here, φ is activation function, $w_{ij}^{(k-1)}$ is weight input from neuron j of the layer of $k-1$ to the neuron i of the layer of k, $y_j^{(k-1)}$ is output of neuron j in the layer of $k-1$.

If input and target data vectors in training set of data are shown as $(x_1, x_2, x_3, \dots, x_n)$ and $(y_1, y_2, y_3, \dots, y_n)$, then the weights of the structure is arranged until each input value $x(k)$ and target output value $y(k)$ is matched with minimized error. For BPA, error between network output and target output can be shown as:

$$E = \sum_{n=1}^{m} ||y_k - y_L||^2 \tag{3.4}$$

Here, y_L is network output vector which corresponds to input vector of $x(k)$.

The beginning point of BPA is setting small random network weights. Then, the weights are arranged to be able to minimize the error, E. The weight and bias values are arranged by the help of gradient descent method:

$$w_{ij}^{(k-1)}(p+1) = w_{ij}^{(k-1)}(p) - \eta \frac{\partial E}{\partial w_{ij}^{(k-1)}} \tag{3.5}$$

$$b_i^k(p+1) = b_i^k(p) - \eta \frac{\partial E}{\partial b_i^k} \tag{3.6}$$

where, η is step size.

Weight updating by use of delta rule, weight and bias values can be arranged with the following equations:

$$w_{ij}^{(k-1)}(p+1) = w_{ij}^{(k-1)}(p) + \eta \delta_i^k y_j^{(k-1)} \tag{3.7}$$

$$b_i^k(p+1) = b_i^k(p) + \eta \delta_i^k \tag{3.8}$$

In Equation 3.7 and 3.8, δ_i^k is error for the i^{th} neuron in k layer. The error in the last layer K can be determined by the equation below:

$$\delta_j^K = \varphi' \left[\sum_{z=1}^{K-1} w_{jz}^{(K-1)} y_z^{(K-1)} + b_j^K \right] \left(y_j - y_j^K \right) \tag{3.9}$$

The error term for the rest of the layers can be defined as:

$$\delta_j^{(k-1)} = \varphi' \left[\sum_{z=1}^{k-2} w_{jz}^{(k-2)} y_z^{(k-2)} + b_j^{(k-1)}\right] \sum_{z=1}^{k} \left(w_{jz}^{k}\right) \delta_z^{k} \quad (3.10)$$

Figure 3.7 shows the flowchart of iterative back-propagation learning procedure.

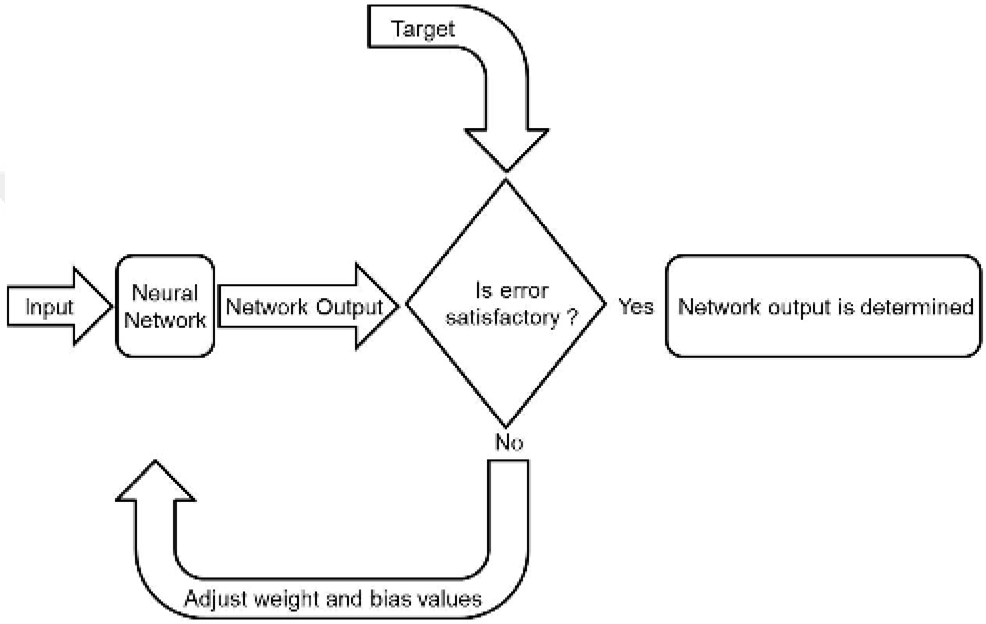


Figure 3.7. Flowchart of BPA

3.1.6. Levenberg–Marquardt Algorithm Derivation

Levenberg–Marquardt Algorithm (LMA) is a supervised BPA which updates weight and bias values according to Levenberg–Marquardt optimization. This algorithm is a mixture of steepest descent method and Gauss-Newton method.

Yu (2011) presented derivation of LMA in four parts as shown below following sections: steepest descent method, Newton’s method, Gauss-Newton’s method and Levenberg-Marquardt algorithm.

Let the object function be sum square error, E to evaluate training process. For all training patterns and outputs:

$$E(x,w) = \frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2 \quad (3.11)$$

here: x and w are input and weight vectors; p is training patterns (from 1 to P); m is outputs (from 1 to M); $e_{p,m}$ is error of training at output m when applying to pattern p.

$$e_{p,m} = d_{p,m} - o_{p,m} \quad (3.12)$$

where: d and o are desired and actual outputs, respectively.

3.1.6.1. Steepest Descent Algorithm

It is first order algorithm which uses first order derivative of total error function for minimizing error space. Gradient, g is defined as in Equation 3.13:

$$g = \frac{\partial E(x,w)}{\partial w} = \left[\frac{\partial E}{\partial w_1}, \frac{\partial E}{\partial w_2}, \dots, \frac{\partial E}{\partial w_N}\right]^T \quad (3.13)$$

The update rule in steepest descent algorithm is:

$$w_k = w_{k+1} - \alpha g_k \quad (3.14)$$

where; α and k are learning constants and training iteration index.

3.1.6.2. Newton’s Method

Assume all gradient components are function of weights and all weights are independent linearly:

$$\begin{aligned} g_1 &= F_1(w_1, w_2, \ldots, w_N) \\ g_2 &= F_2(w_1, w_2, \ldots, w_N) \\ g_3 &= F_3(w_1, w_2, \ldots, w_N) \end{aligned} \tag{3.15}$$

With first order approximation and Taylor series expand each g_i:

$$\begin{aligned} g_1 &\approx g_{1,0} + \frac{\partial g_1}{\partial w_1}\Delta w_1 + \frac{\partial g_1}{\partial w_2}\Delta w_2 + \cdots + \frac{\partial g_1}{\partial w_N}\Delta w_N \\ g_2 &\approx g_{2,0} + \frac{\partial g_2}{\partial w_1}\Delta w_1 + \frac{\partial g_2}{\partial w_2}\Delta w_2 + \cdots + \frac{\partial g_2}{\partial w_N}\Delta w_N \\ g_N &\approx g_{N,0} + \frac{\partial g_N}{\partial w_1}\Delta w_1 + \frac{\partial g_N}{\partial w_2}\Delta w_2 + \cdots + \frac{\partial g_N}{\partial w_N}\Delta w_N \end{aligned} \tag{3.16}$$

By combining Equation 3.13:

$$\frac{\partial g_i}{\partial w_i} = \frac{\partial\left(\frac{\partial E}{\partial w_i}\right)}{\partial w_j} = \frac{\partial^2 E}{\partial w_i \partial w_j} \tag{3.17}$$

where: i and j are weights indices from 1 to N.

Insert Equation 3.17 into 3.16:

$$\begin{aligned} g_1 &\approx g_{1,0} + \frac{\partial^2 E}{\partial w_1^2}\Delta w_1 + \frac{\partial^2 E}{\partial w_1 \partial w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_1 \partial w_N}\Delta w_N \\ g_2 &\approx g_{2,0} + \frac{\partial^2 E}{\partial w_2 \partial w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_2^2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_2 \partial w_N}\Delta w_N \\ g_N &\approx g_{N,0} + \frac{\partial^2 E}{\partial w_N \partial w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_N \partial w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_N^2}\Delta w_N \end{aligned} \tag{3.18}$$

To make total error function E minimum, each gradient vector element must be zero.

$$
\begin{aligned}
0 &\approx g_{1,0} + \frac{\partial^2 E}{\partial w_1^2}\Delta w_1 + \frac{\partial^2 E}{\partial w_1 \partial w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_1 \partial w_N}\Delta w_N \\
0 &\approx g_{2,0} + \frac{\partial^2 E}{\partial w_2 \partial w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_2^2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_2 \partial w_N}\Delta w_N \\
&\cdots \\
0 &\approx g_{N,0} + \frac{\partial^2 E}{\partial w_N \partial w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_N \partial w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_N^2}\Delta w_N
\end{aligned}
\tag{3.19}
$$

Then, combine Equation 3.13 and 3.19:

$$
\begin{aligned}
-\frac{\partial E}{\partial w_1} &\approx -g_{1,0} + \frac{\partial^2 E}{\partial w_1^2}\Delta w_1 + \frac{\partial^2 E}{\partial w_1 \partial w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_1 \partial w_N}\Delta w_N \\
-\frac{\partial E}{\partial w_2} &\approx -g_{2,0} + \frac{\partial^2 E}{\partial w_2 \partial w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_2^2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_2 \partial w_N}\Delta w_N \\
&\cdots \\
-\frac{\partial E}{\partial w_N} &\approx -g_{N,0} + \frac{\partial^2 E}{\partial w_N \partial w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_N \partial w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_N^2}\Delta w_N
\end{aligned}
\tag{3.20}
$$

Now, we have N equations and N parameters to calculate all of the Δw_i.

$$\begin{bmatrix} -g_1 \\ -g_2 \\ \ldots \\ -g_3 \end{bmatrix} = \begin{bmatrix} -\frac{\partial E}{\partial w_1} \\ -\frac{\partial E}{\partial w_2} \\ \ldots \\ -\frac{\partial E}{\partial w_N} \end{bmatrix} = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\ \frac{\partial^2 E}{\partial w_2 \partial w_1} & \frac{\partial^2 E}{\partial w_2^2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial^2 E}{\partial w_N \partial w_1} & \frac{\partial^2 E}{\partial w_N \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_N^2} \end{bmatrix} x \begin{bmatrix} \Delta w_1 \\ \Delta w_2 \\ \ldots \\ \Delta w_N \end{bmatrix} \tag{3.21}$$

This square matrix (NxN) is Hessian matrix, H.

$$H = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\ \frac{\partial^2 E}{\partial w_2 \partial w_1} & \frac{\partial^2 E}{\partial w_2^2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial^2 E}{\partial w_N \partial w_1} & \frac{\partial^2 E}{\partial w_N \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_N^2} \end{bmatrix} \tag{3.22}$$

Combine Equation 3.13, 3.21 and 3.22:

$$-g = H\Delta w \tag{3.23}$$

$$\Delta w = -H^{-1} g \tag{3.24}$$

Therefore update rule becomes:

$$w_{k+1} = w_k - H_k^{-1} g_k \tag{3.25}$$

3.1.6.3. Gaussian-Newton Algorithm

In Newton's method, updating weights needs to be calculated second order derivatives of total error function to obtain Hessian matrix. It is very complex work. To make calculations simpler, define Jacobian matrix, J:

$$J = \begin{bmatrix} \frac{\partial e_{1,1}}{\partial w_1} & \frac{\partial e_{1,1}}{\partial w_2} & \cdots & \frac{\partial e_{1,1}}{\partial w_N} \\ \frac{\partial e_{1,2}}{\partial w_1} & \frac{\partial e_{1,2}}{\partial w_2} & \cdots & \frac{\partial e_{1,2}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{1,M}}{\partial w_1} & \frac{\partial e_{1,M}}{\partial w_2} & \cdots & \frac{\partial e_{1,M}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{P,1}}{\partial w_1} & \frac{\partial e_{P,1}}{\partial w_2} & \cdots & \frac{\partial e_{P,1}}{\partial w_N} \\ \frac{\partial e_{P,2}}{\partial w_1} & \frac{\partial e_{P,2}}{\partial w_2} & \cdots & \frac{\partial e_{P,2}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{P,M}}{\partial w_1} & \frac{\partial e_{P,M}}{\partial w_2} & \cdots & \frac{\partial e_{P,M}}{\partial w_N} \end{bmatrix} \tag{3.26}$$

Integrate 3.11 and 3.13 and obtain each gradient vector element as:

$$g_i = \frac{\partial E}{\partial w_i} = \frac{\partial \left(\frac{1}{2} \sum_{p=1}^{P} \sum_{m=1}^{M} e_{p,m}^2 \right)}{\partial w_i} = \sum_{p=1}^{P} \sum_{m=1}^{M} \frac{\partial e_{p,m}}{\partial w_i} e_{p,m} \tag{3.27}$$

Combine Equation 3.26 and 3.27 and:

$$g = Je \tag{3.28}$$

Then, the error function:

$$e = \begin{bmatrix} e_{1,1} \\ e_{1,2} \\ \cdots \\ e_{1,M} \\ \cdots \\ e_{P,1} \\ e_{P,2} \\ \cdots \\ e_{P,M} \end{bmatrix} \tag{3.29}$$

Insert 3.11 into 3.22, each element (ith row, jth columun) of Hessian matrix can be calculated as:

$$h_{i,j} = \frac{\partial^2 E}{\partial w_i \partial w_j} = \frac{\partial^2 \left(\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2\right)}{\partial w_i \partial w_j} = \sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\partial e_{p,m}}{\partial w_i}\frac{\partial e_{p,m}}{\partial w_j} + S_{i,j} \tag{3.30}$$

$$S_{i,j} = \sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\partial^2 e_{p,m}}{\partial w_i \partial w_j} e_{p,m} \tag{3.31}$$

As the basic assumption of Newton's method $S_{i,j}$ is closed to zero, relation between Hessian matrix and Jacobian matrix can be defined as:

$$H = J^T J \tag{3.32}$$

Combine Equation 3.25, 3.28 and 3.32 for updating rule of Gauss-Newton algorithm:

$$w_{k+1} = w_k - \left(J_k^T J_k\right)^{-1} J_k e_k \tag{3.33}$$

3.1.6.4. Levenberg-Marquardt Algorithm

In order to make sure that approximated Hessian matrix, $J^T J$, is invertible, LMA introduces another approximation to Hessian matrix:

$$H = J^T J + \mu I \quad (3.34)$$

where: μ is always positive, combination coefficient, I is identity matrix.

From equation 3.34, we can notice that the elements on the main diagonal of the approximated Hessian matrix will be larger than zero. So, with approximation (Equation 3.34), it can be sure that Hessian matrix is always invertible. By combining Equation 3.33 and 3.34, the update rule of LMA becomes:

$$w_{k+1} = w_k - \left(J_k^T J_k + \mu I\right)^{-1} J_k e_k \quad (3.35)$$

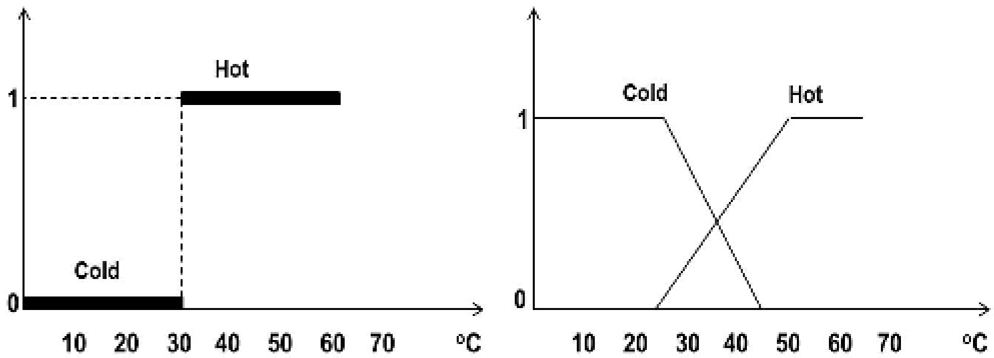
3.2. Fuzzy Logic and Fuzzy Expert Systems

Logic is science of formal principles of reasoning. On the other hand, fuzzy logic (FL) is relevant with approximate reasoning. In fuzzy case, the precise reasoning can be thought as limit case (Zadeh, 1988).

The word fuzzy has meanings of cloudy, vague. Therefore, FL contains uncertainties or it works with uncertainties. The real world we lived has lots of uncertainties. It means that, we have to study these uncertainties in order to figure out the ability of human to reach conclusions (Semerci, 2004).

Classical logic (CL) is represented with 0 and 1 for truth values. It means that the variables can only be assigned as either true or false. This situation brings some problems when we deal with complex systems. FL can solve these problems by assigning truth values between 0 and 1. These can be directed by using linguistic variables with different membership functions (Tütüncü, 2009).

Figure 3.8 shows examples for modelling with classical and fuzzy logic. According to CL, each temperature level belongs to certain sets, hot or cold. For example, according to this logic, 30 ^oC is a boundary for judgement on temperature's being whether hot or cold. Temperatures below 30 ^oC are stated as cold, above 30 ^oC are stated as hot (Figure 3.8a). Therefore, 29.9 ^oC temperature can be stated as cold according to CL. Difference between 29.9-30 ^oC is very low but very important for CL. But in physical world, this difference is unimportant. 29.9 ^oC cannot reject being hot. FL removes these sharp borders. While CL says 29.9 ^oC is cold, FL says it is fairly hot. In CL, there are only hot or cold sets. On the other hand, FL can accept statements as fairly cold, fairly hot etc. besides cold and hot sets and tries to explain them mathematically. Here, cold, hot, fairly cold, fairly hot terms are linguistic variables. The values of these linguistic variables can be expressed with fuzzy sets (Tütüncü, 2009).



(a) (b)

Figure 3.8. Example for (a) classical logic (b) fuzzy logic model

Fuzzy expert systems (FES) can be constructed by use of FL that related with uncertainties. These systems use fuzzy sets and imitate human reasoning process. Decision making process does not consist of only black and white (true-false). This process commonly contains grey areas. Therefore, we need this type of approach (Liao, 2005). FES uses a set of fuzzy if-then rules with FIS in order to make decisions (Fialho et al., 2016).

3.3. Adaptive Neuro Fuzzy Inference System (ANFIS)

Modelling system with differential equations (conventional mathematics) is not suitable for uncertain systems. On the other hand, systems with fuzzy inference which contains a set of if-then rules are able to model human reasoning and knowledge process with qualitatively. First systematic study on fuzzy modelling or identification was achieved by Takagi and Sugeno (Jang, 1993).

ANFIS constructs fuzzy if-then rules with proper membership functions to generate input-output pairs (Jang, 1993). Working principle of ANFIS is alike with ANN. It learns knowledge from a data set for the fuzzy modelling method. Fuzzy rules connect system inputs and outputs in form of if-then expressions and depending on linguistic variables (Ay and Kisi, 2014). A fuzzy inference system can be seen from Figure 3.9.

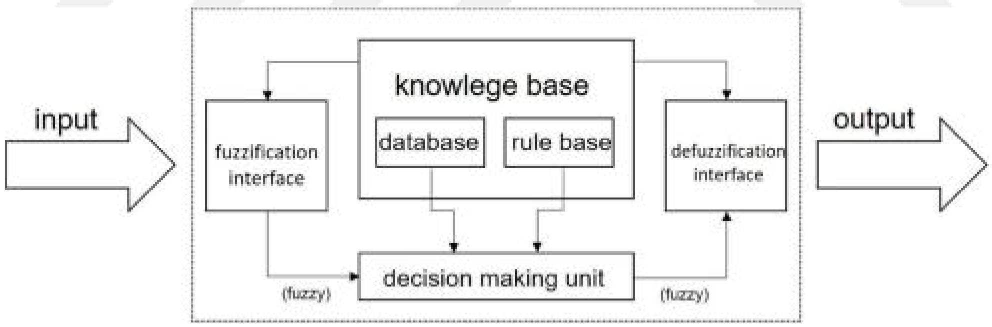


Figure 3.9. Fuzzy inference system (Jang, 1993)

There are various types of fuzzy reasoning in literature. Figure 3.10 shows most commonly used FIS.

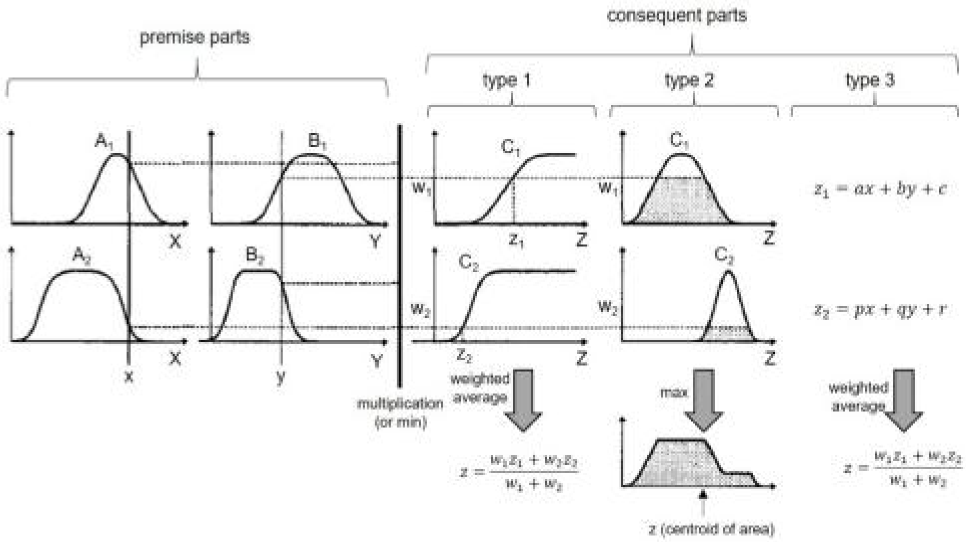


Figure 3.10. Various types of fuzzy reasoning structures and if-then rules (Jang, 1993)

ANFIS is mix of fuzzy systems and neural networks. In this structure, neural network is utilized for determining of fuzzy system parameters. The system parameters are automatically arranged by neural network. Learning ability advantage of neural network and advantages of rule-based fuzzy system are able to enhance system performance. In neuro-fuzzy systems FL statements builds the system, then, it is refined by use of training algorithm of neural network (Rai et al., 2015).

3.3.1. ANFIS Structure

Jang (1993) demonstrated main structure of ANFIS as summarized below in detail:

Assume there is two inputs (x, y) and one output (z) FIS. Suppose that, there are two Takagi and Sugeno's type if-then rules:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

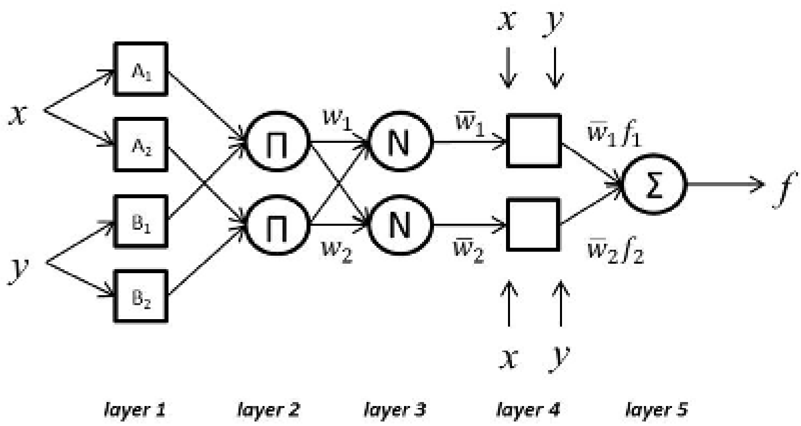


Figure 3.11. Equivalent ANFIS structure of type-3 fuzzy reasoning

Layer 1: Each node (i) in this layer is square and has a node function of:

$$O_i^1 = \mu A_i(x) \tag{3.36}$$

where, x is input to node i, A_i is linguistic variable (small, big etc.). O_i^1 is membership function of A_i. Generally, bell-shaped with maximum of 1 and minimum of 0 membership function is selected:

$$\mu A_i(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{3.37}$$

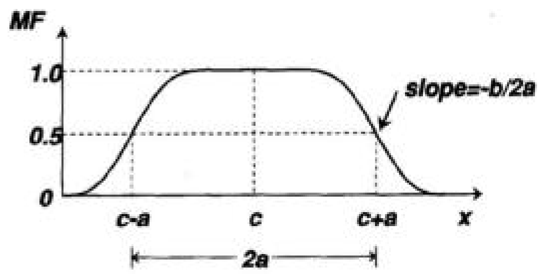


Figure 3.12. Bell shaped membership function parameters (Jang, 1993)

a_i, b_i and c_i are parameter sets and they are called as premise parameters.

Layer 2: Each node in this layer is circle. This node multiplies incoming signals and generates output:

$$w_i = \mu A_i(x) * \mu B_i(y) \tag{3.38}$$

where $i = 1, 2$.

Layer 3: Each node in this layer is circle. The node i calculates the ratio of firing strength of rule i and firing strength of all rules summations.

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{3.39}$$

where $i = 1, 2$.

Layer 4: Each node in this layer is square. Node function is:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \tag{3.40}$$

where, $\bar{w}_i$ is output of 3rd layer. p_i, q_i and r_i are parameter sets and they are called as consequent parameters.

Layer 5: The node is circle and it calculates overall output:

$$O_i^5 = overall\ output = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{3.41}$$

The learning algorithm tries to arrange premise (a_i, $b_{i,}$ c_i) and consequent (p_i, $q_{i,}$ r_i) parameters to obtain optimum results as ANFIS output (Valcic et al., 2011).

3.4. Regression Analysis

Regression analysis is a technique that sets a functional relation between dependent and independent variables. It is a statistical method that exhibits relationships between variables.

3.4.1. Linear Regression

Assume we have a set of data pairs as (x_1, y_1), (x_2, y_2), …, (x_n, y_n) and fit a straight line for least-square approximation through these data pairs. The equation of straight line mathematically (Chapra and Canale, 2010):

$$y = a_0 + a_1 x + e \tag{3.42}$$

where a_0 and a_1 are intercept and slope coefficients and e is error between model and observed data. The error can be defined as:

$$e = y - a_0 - a_1 x \tag{3.43}$$

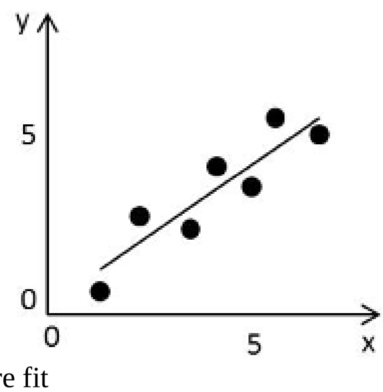


Figure 3.13. Least-square fit

It is obvious that the sum of the errors for all data points must be minimized in order to obtain best fitted line (Figure 3.13).

$$\sum_{i=1}^{n} e_i = \sum_{i=1}^{n} (y_i - a_0 - a_1 x_i) \tag{3.44}$$

where n is total data number.

This approximation brings some deficiencies when calculating total error. Therefore, some of the squares of differences between measured and calculated output can overcome deficiencies and it can be expressed as:

$$S_r = \sum_{i=1}^{n} {e_i}^2 = \sum_{i=1}^{n} \left(y_{i,measured} - y_{i,model}\right)^2 = \sum_{i=1}^{n} (y_i - a_0 - a_1 x_i)^2 \tag{3.45}$$

Equation 3.45 must be differentiated with respect to a_0 and a_1 in order to find the values of these coefficients:

$$\frac{\partial S_r}{\partial a_0} = -2 \sum (y_i - a_0 - a_1 x_i) \tag{3.46}$$

$$\frac{\partial S_r}{\partial a_1} = -2 \sum [(y_i - a_0 - a_1 x_i) x_i] \tag{3.47}$$

Set Equation 3.46 and 3.47 zero in order to obtain minimum of S_r:

$$0 = \sum y_i - \sum a_0 - \sum a_1 x_i \tag{3.48}$$

$$0 = \sum y_i x_i - \sum a_0 x_i - \sum a_1 {x_i}^2 \tag{3.49}$$

Knowing that, $\sum a_0 = na_0$:

$$na_0 + \left(\sum x_i\right) a_1 = \sum y_i \tag{3.50}$$

$$\left(\sum x_i\right) a_0 + \left(\sum {x_i}^2\right) a_1 = \sum x_i y_i \tag{3.51}$$

Then:

$$a_1 = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{n \sum {x_i}^2 - (\sum x_i)^2} \tag{3.52}$$

$$a_0 = \overline{y} - a_1 \overline{x} \tag{3.53}$$

Here, $\overline{x}$ and $\overline{y}$ are mean values of x and y.

3.4.2. Non-linear Regression and Linearization

Relationship between dependent and independent variables may not be linear many times. For example, nonlinear model can be expressed as shown below (Chapra and Canale, 2010):

$$y = a_1 x^{\beta_1} \tag{3.54}$$

Where, a_1 and β_1 are constant coefficients.

There are non-linear regression techniques available to apply experimental data directly. But there are easier alternatives as transforming equations into linear form. Then, linear regression can be used for fitting purpose (Chapra and Canale, 2010). Equation 3.54 can be linearized by taking logarithm of both sides:

$$logy = \beta_1 logx + loga_1 \tag{3.55}$$

Figure 3.14 summarizes the linearized forms of nonlinear equations:

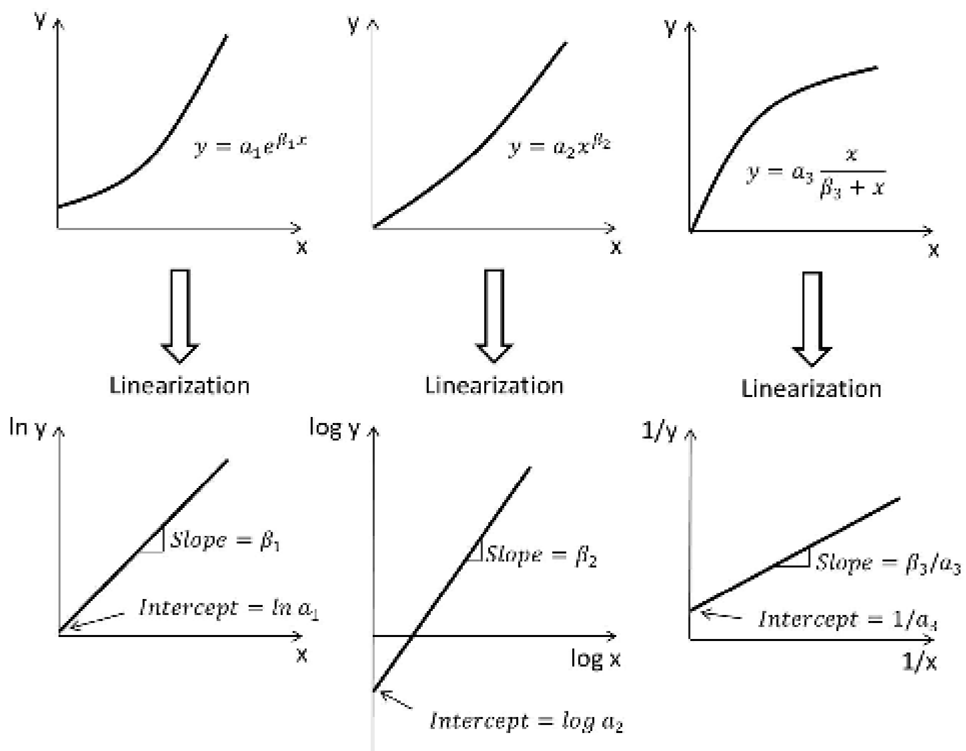


Figure 3.14. Linearized forms of nonlinear equations (Chapra and Canale, 2010)

4. RESULTS AND DISCUSSION

4.1. Prediction of Engine-Out Parameters of a Diesel Engine Operated with Biodiesel – Alcohol Blends (Model 1)

In Model 1, performance and emission engine out-parameters which are torque, carbon monoxide (CO) and oxides of nitrogen (NO_x) were estimated by using LR and ANN. The engine used for tests is naturally aspirated compression ignition engine and it was operated with pure diesel, peanut oil biodiesel and alcohol-biodiesel blends (20% ethanol - 80% peanut oil biodiesel; 20% methanol - 80% peanut oil biodiesel; 20% butanol - 80% peanut oil biodiesel). Table 4.1 and Table 4.2 show technical details of diesel engine and hydraulic dynamometer (Tosun et al., 2014).

Table 4.1. Engine specifications in Model 1

Brand	**Mitsubishi Canter**
Model	4D34-2A
Configuration	In line 4
Type	Direct injection diesel with glow plug
Displacement	3907 cc
Bore	104 mm
Stroke	115 mm
Power	89 kW @ 3200 rpm
Torque	295 Nm @ 1800 rpm
Oil cooler	Water cooled
Air cleaner	Paper element type
Weight	325 kg

Table 4.2. Dynamometer specifications in Model 1

Torque Range	0-1700 Nm
Speed Range	0-7500 rpm
Body Weight	45 kgf
Total Weight	110 kgf
Body Diameter	350 mm
Torque Arm Length	350 mm

Beside engine studies, fuel properties of each fuel and fuel blends were determined. In this way, Zeltex ZX440, IKA-Werke C2000 Bomb Calorimeter and Kyoto Electronics DA-130 devices were used to measure cetane number, lower heating value and density values of each fuel, respectively.

A data set was obtained by operating engine with different engine speeds and fuels (Tosun et al., 2014). Some of these data were used for training purpose of prediction models. Remaining data were used to test the performance of the model. Engine torque, CO and NO_x were predicted (output) values whereas engine speed, cetane number, heating value and density of fuels were inputs.

Regression analysis is widely used to define relation between two or more variables. SPSS (Statistical Package for the Social Sciences) is one of the useful statistical package programs in order to perform regression analysis. Therefore, it was selected for regression analysis.

To construct models total data set were divided into two main sections: training and testing. 80% of data were used for training purpose and remaining randomly selected 20% of data were used for testing purpose. Table 4.3 shows the details of linear regression analysis. Following Figure 4.1, 4.2 and 4.3 demonstrate the graphical representation of prediction performance of equations.

Table 4.3. Linear regression results of Model 1

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

$$y = \beta_0 + \beta_1(engine\ speed) + \beta_2(cetane\ number) + \beta_3(heating\ value) + \beta_4(density)$$

y	β_0	β_1	β_2	β_3	β_4	R^2
$Torque$	543.357	-0.102	-0.239	0.05	-0.448	0.726
CO	-827.513	0.257	-4.194	0.01	0.685	0.898
NO_x	4621.616	-0.611	8.886	-0.024	-2.702	0.919

Train data was used to constitute regression equation given above Table 4.3. Remaining test data shows the prediction ability of equations.

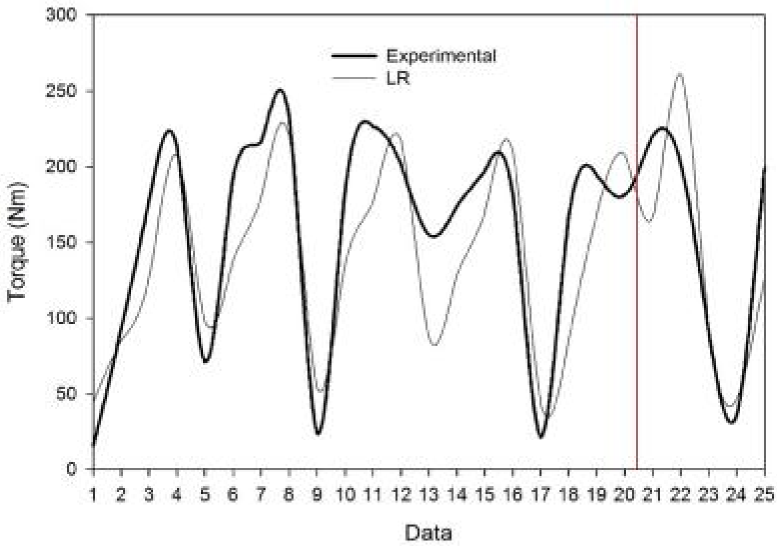


Figure 4.1. Experimental vs linear regression prediction of torque for Model 1

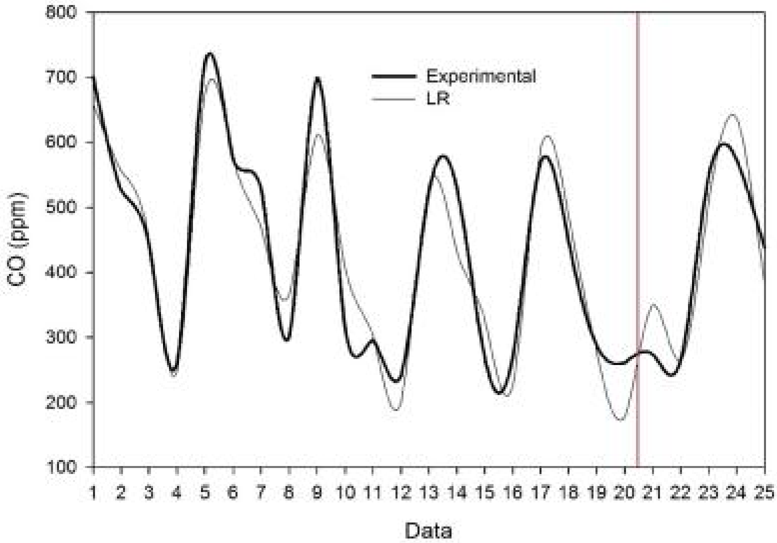


Figure 4.2. Experimental vs linear regression prediction of CO for Model 1

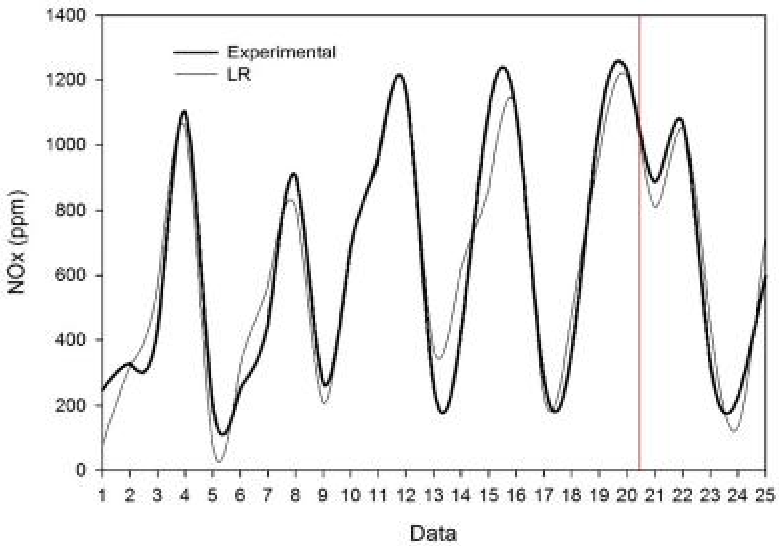


Figure 4.3. Experimental vs linear regression prediction of NO_x for Model 1

In ANN modelling, MATLAB (matrix laboratory) software was used. MATLAB contains artificial neural network toolbox. Main structure of ANN model consists of three layers: input, hidden and output. Figure 4.4 shows the architecture used in ANN in Model 1. As seen from the figure below that, information is flowing through forward way. Signals coming from external world enter to the structure, they are processed and an output signal is generated. Information is conveyed via neurons and connection between neurons called as weights.

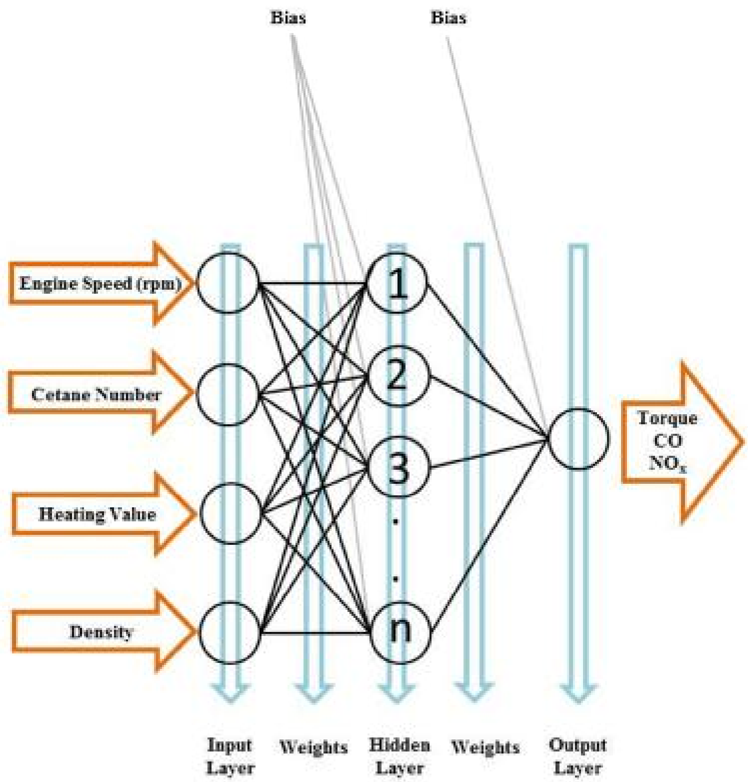


Figure 4.4. ANN structure in Model 1

Determining best ANN structure has some important points as selection of learning algorithm, transfer functions, number of hidden layer, number of neurons in hidden layer etc.

Selection of learning algorithm is important issue for ANN training. Levenberg-Marquardt which is back-propagation algorithm was selected as learning algorithm in this model in order to arrange and optimize the weights for obtaining more close values to target values. Although some other algorithms were tried, LMA gave best accurate results. Selection of proper transfer functions is another important issue. Logistic sigmoid function (logsig) for hidden layer and linear function (purelin) for output layer were utilized as transfer functions. Number of hidden layer neuron is usually determined by trial and error method

(Togun and Baysec, 2010). General structure of ANN can be stated as 4-n-1 (Figure 4.4). Since all outputs are evaluated alone, number of output neuron is 1. Here, n is number of neuron in hidden layer. The values of n are 7, 9 and 13 for torque, CO, NO_x predictions, respectively. Prediction equations for all outputs were given in Table 4.4. On the other hand, related weight and bias values can be seen from Table 4.5, 4.6 and 4.7.

Table 4.4. Mathematical background behind ANN predictions for Model 1

$$Torque = -7.9755 * F_1 + 27.0340 * F_2 - 93.3236 * F_3 + 96.4421 * F_4 + 5.7018 * F_5 - 24.3317 * F_6 + 30.9032 * F_7 + 117.7479$$

$$CO = 47.4444 * F_1 - 191.1111 * F_2 - 142.2222 * F_3 + 32.5236 * F_4 + 388.4580 * F_5 + 83.6667 * F_6 + 99.1133 * F_7 - 188.3333 * F_8 - 148.1111 * F_9 + 391.2086$$

$$NOx = 0.5306 * F_1 + 21.6029 * F_2 - 0.1043 * F_3 + 50.1298 * F_4 + 453.4412 * F_5 - 28 * F_6 + 274.7941 * F_7 + 1.9096 * F_8 + 0.3404 * F_9 + 40.7623 * F_{10} + 49.5639 * F_{11} + 48.6242 * F_{12} + 48.8891 * F_{13} + 49.0307$$

$$F_i = \frac{1}{1 + e^{-E_i}}$$

$$E_i = W_{1i} * (engine\ speed) + W_{2i} * (cetane\ number) + W_{3i} * (heating\ value) + W_{4i} * (\text{density}) + b_i$$

Table 4.5. Weight and bias values between input and hidden layer for torque prediction of Model 1

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	*i*	b_i
1	3.3305	-97.6738	-0.6992	29.3846	1	-104.3517
2	-4.3771	-41.3274	-39.9587	8.4538	2	114.1732
3	5.3781	97.5159	-0.2034	-11.4652	3	50.2300
4	-4.3680	-1.7581	0.1965	4.7418	4	33.8932
5	0.0228	-5.1877	-0.6637	30.2536	5	-151.2201
6	-2.4200	0.4794	-0.3408	21.5033	6	5.4968
7	-0.6102	-0.3744	0.0480	-6.2920	7	-61.9001

Table 4.6. Weight and bias values between input and hidden layer for CO prediction of Model 1

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	*i*	b_i
1	6.3035	1.4295	-0.3935	3.1566	1	80.4540
2	-2.3156	-0.7944	-0.4867	30.3244	2	-95.9337
3	-16.4184	-0.5451	1.0430	-2.0841	3	-148.1982
4	2.9497	0.7705	0.0647	-14.6638	4	15.6436
5	-0.5917	6.2499	0.0716	2.9751	5	-154.8052
6	14.5499	0.0468	-0.6872	-2.3568	6	112.0702
7	-7.1104	0.1483	-115.7263	-26.0755	7	-143.7120
8	-24.4875	-2.1424	1.1956	-15.1036	8	45.1141
9	39.7832	-1.4110	-1.3627	3.2666	9	97.9484

Table 4.7. Weight and bias values between input and hidden layer for NO_x prediction of Model 1

i	W_{1i}	W_{2i}	W_{3i}	W_{4i}	*i*	b_i
1	-12.5133	0.5029	0.3404	0,0696	*1*	-159.0413
2	-42.8641	-0.1102	2.3541	0,4106	*2*	72.4009
3	19.3421	0.5260	-1.8624	-0,4460	*3*	-90.5721
4	18.4471	0.0224	-0.2913	3,1840	*4*	40.9710
5	-3.8993	1.5954	0.2406	-3,2165	*5*	-185.5012
6	12.1997	0.1933	-0.7819	-4,3650	*6*	52.6386
7	-6.5627	0.5023	-0.1990	23,8889	*7*	95.3561
8	-62.6611	-0.5614	3.8057	5,5248	*8*	-73.5869
9	-1.4964	1.2212	0.1476	-2,2288	*9*	-138.0217
10	-6.3243	0.0669	0.7237	-10,0390	*10*	132.3532
11	-15.119	-0.4025	1.6381	-0,2028	*11*	-67.4554
12	10.993	-0.3894	-0.1040	1,1023	*12*	-41.4348
13	1.7183	-0.5865	0.4811	-0,4410	*13*	46.9212

Both ANN and experimental results were given in the following Figures 4.5, 4.6 and 4.7.

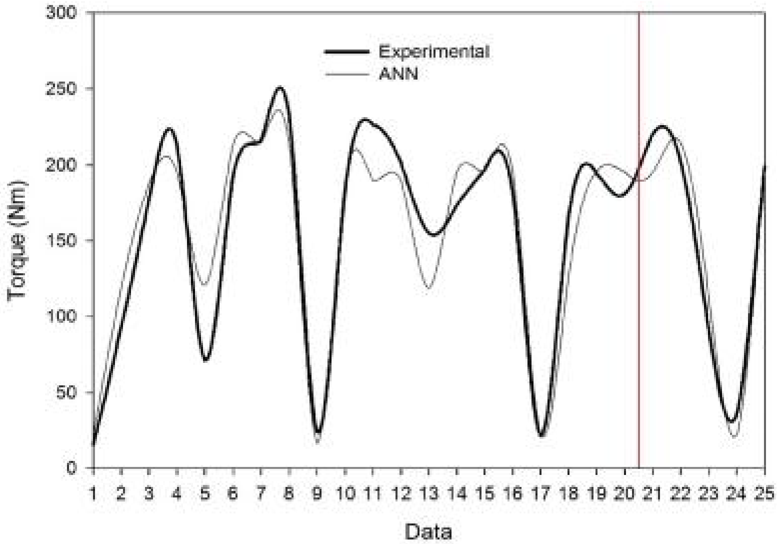


Figure 4.5. Experimental vs ANN prediction of torque for Model 1

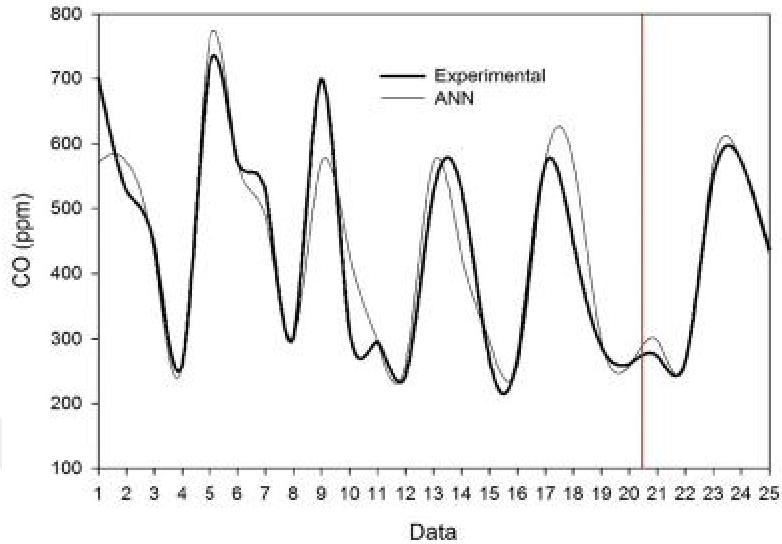


Figure 4.6. Experimental vs ANN prediction of CO for Model 1

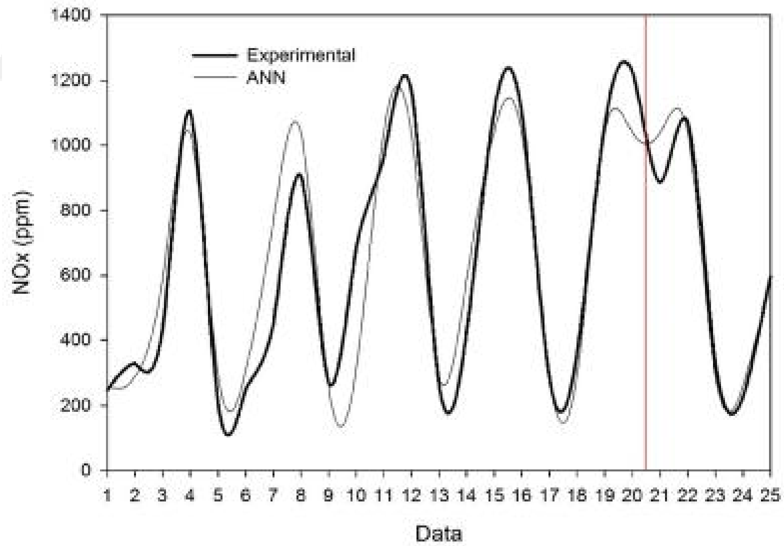


Figure 4.7. Experimental vs ANN prediction of NO_x for Model 1

As seen from the above figures, ANN gives more satisfactory results for prediction of various engine-out parameters. It means that ANN can be suggested to estimate engine output parameters quickly in order to eliminate time consuming and costly experiments.

There are various types of performance evaluation criterions to observe convergence between target and predicted values as mean error, mean absolute error, root mean square error, and mean absolute percentage error etc. (Bilgili and Sahin, 2010)

Mean absolute percentage error (MAPE) was selected to see model performances for predictions. MAPE can be expressed as stated in Equation 4.1 (Yasar et al., 2012).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|o_i - t_i|}{t_i}.100 \tag{4.1}$$

Table 4.8. Prediction performance evaluation for Model 1

	MAPE	
	LR	ANN
Torque	24.96	16.22
CO	11.9	3.56
NO_x	22.1	9.63

Typical MAPE values on the basis of forecasting ability were given in Table 4.9 (Emang et al., 2010).

Table 4.9. MAPE values for model evaluation

MAPE (%)	***Evaluation***
MAPE ≤ 10%	High Accuracy Forecasting
10% < MAPE ≤ 20%	Good Forecasting
20% < MAPE ≤ 50%	Reasonable Forecasting
MAPE > 50%	Inaccurate Forecasting

Although ANN results are satisfactory, the prediction performance can obviously be enhanced with using more data during training period. Training with more data will increase generalization capacity of model.

4.2. Prediction of Engine-Out Parameters of a Diesel Engine Operated by Diesel Fuel with Nanoparticle Additives (Model 2)

In Model 2, engine performance and emission (torque, CO, CO_2 and NO_x) estimations by using various techniques were conducted. The engine and dynamometer are same in Model 1 and the specifications can be seen from Table 4.1 and 4.2. Engine tests were done by Ozgur (2011). He investigated various nanoparticle additives (MgO, Al_2O_3, Fe_2O_3, NiO, $Zn_{0.5}Ni_{0.5}Fe_2O_4$ etc.) effects to conventional diesel and alternative biodiesel. Both changes in fuel properties and changes in performance and emission results were observed with use of nanoparticle additives. Details of the experiments can be found in study of Ozgur (2011). His study was conducted with various types of nanoparticle additions into both diesel and biodiesel fuels and also with various dosages of nanoparticle additives. In here, only diesel - MgO, diesel - Al_2O_3, diesel - Fe_2O_3, diesel - NiO and diesel - $Zn_{0.5}Ni_{0.5}Fe_2O_4$ (100 ppm dosage of each nanoparticle) blend results were used.

By using experimental results, the total data set was divided into two groups: training and testing as in previous Model 1. Total data set (54) contain five blends. 85% of total data (46) was used for training purpose. Remaining randomly selected 15% of data (8) was used to test and evaluate the performance of the model. Estimated engine-out parameters are torque, CO, NO_x and CO_2 whereas cetane number and engine speed are inputs. Zeltex ZX440 device was used to determine cetane number of each blend.

Table 4.10 and 4.11 show the regression coefficients of linear and non-linear regression equations. Following Figure 4.8, 4.9 and 4.10 demonstrate the graphical representation of experimental and regression results.

Table 4.10. Linear regression results of Model 2

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

$$y = \beta_0 + \beta_1(cetane\ number) + \beta_2(engine\ speed)$$

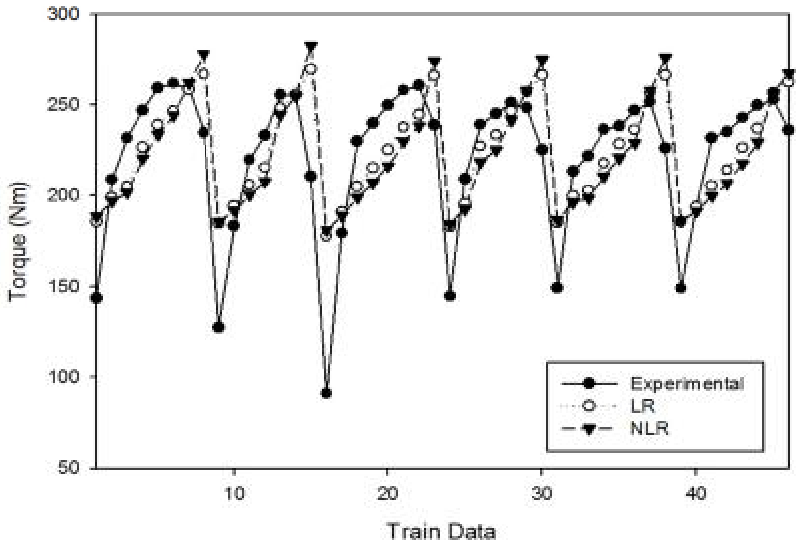
$\boldsymbol{y}$	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$
$Torque$	322.063	0.09	-0.05
CO	109.993	-1.228	0.099
NO_x	1288.835	5.489	-0.247
CO_2	8.726	0.03	-0.002

Table 4.11. Non-linear regression results of Model 2

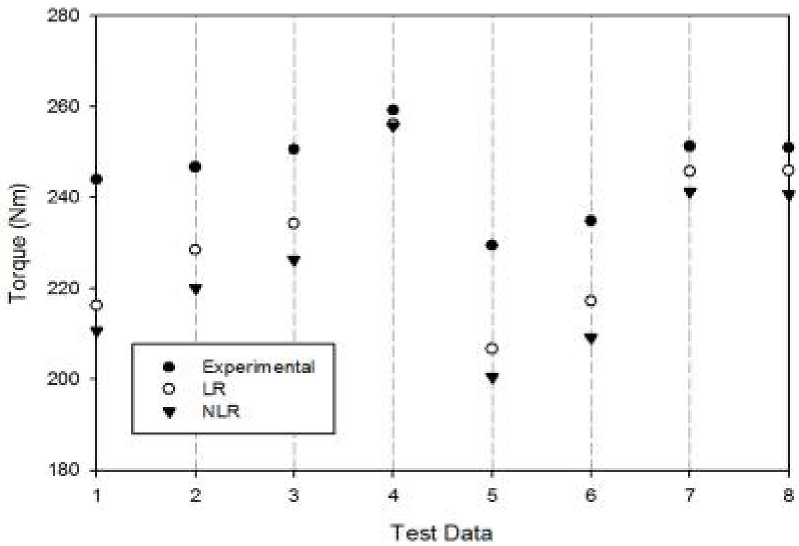
$$y = \alpha_0({x_1}^{\alpha_1})({x_2}^{\alpha_2})$$

$$y = \alpha_0(cetane\ number^{\alpha_1})(engine\ speed^{\alpha_2})$$

$\boldsymbol{y}$	$\boldsymbol{\alpha_0}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$
$Torque$	5727.96	0.054	-0.457
CO	2.818	-0.089	0.636
NO_x	11614.49	0.325	-0.484
CO_2	66.37	0.255	-0.428

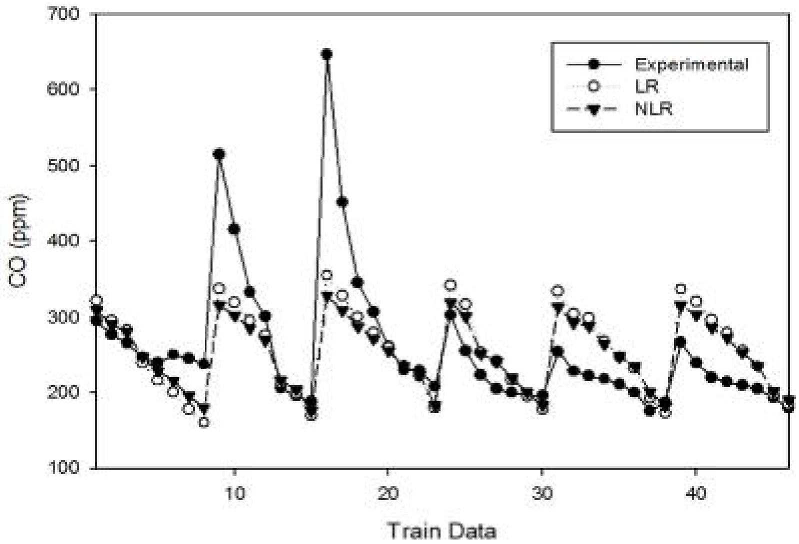


(a)

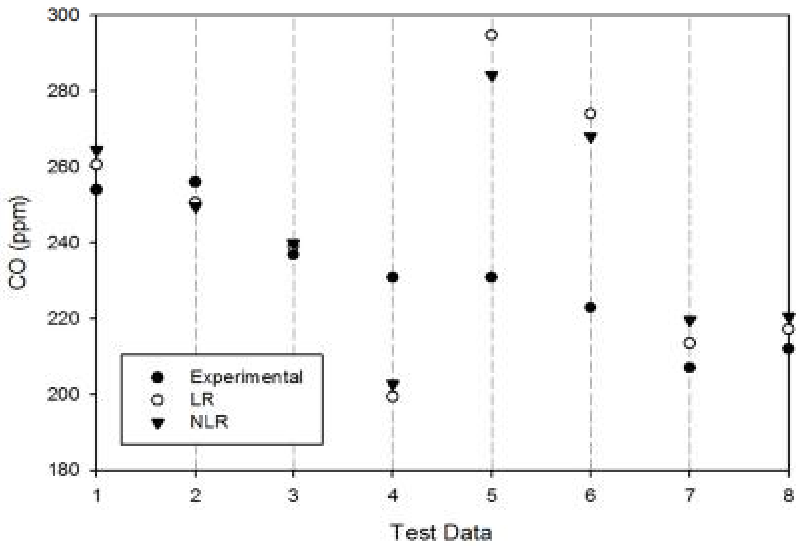


(b)

Figure 4.8. (a) Training (b) testing section of torque prediction with regression analysis for Model 2

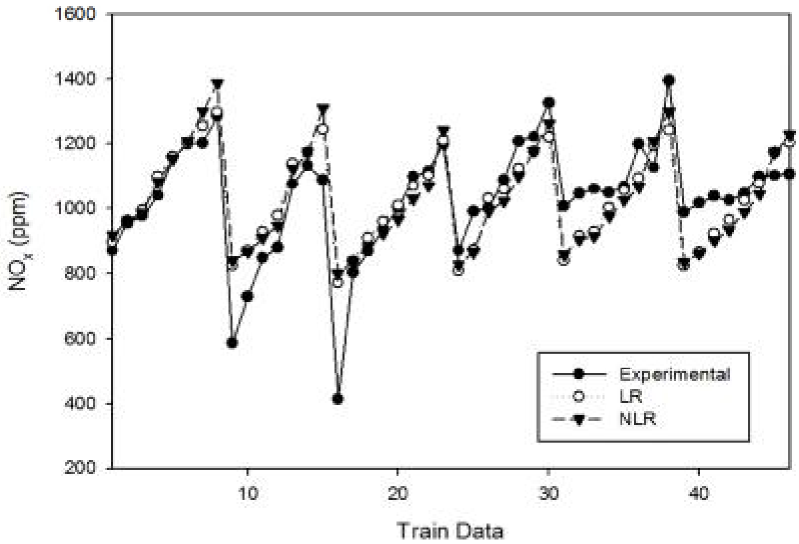


(a)

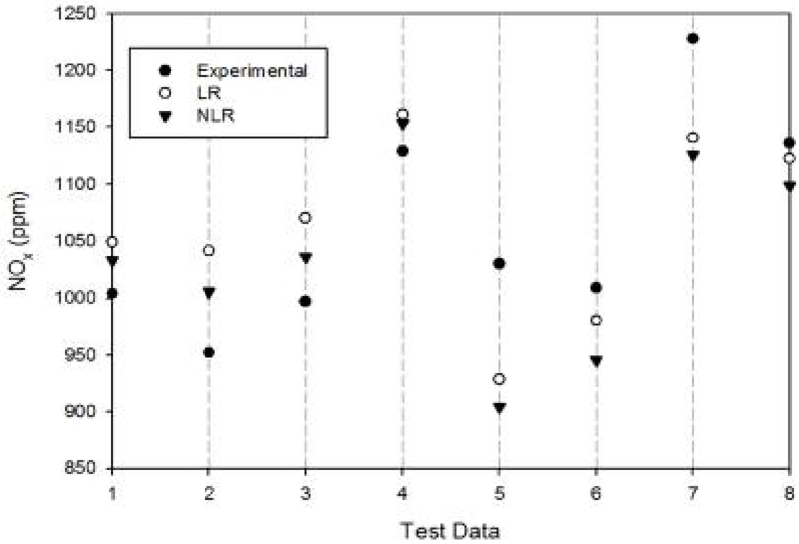


(b)

Figure 4.9. (a) Training (b) testing section of CO prediction with regression analysis for Model 2

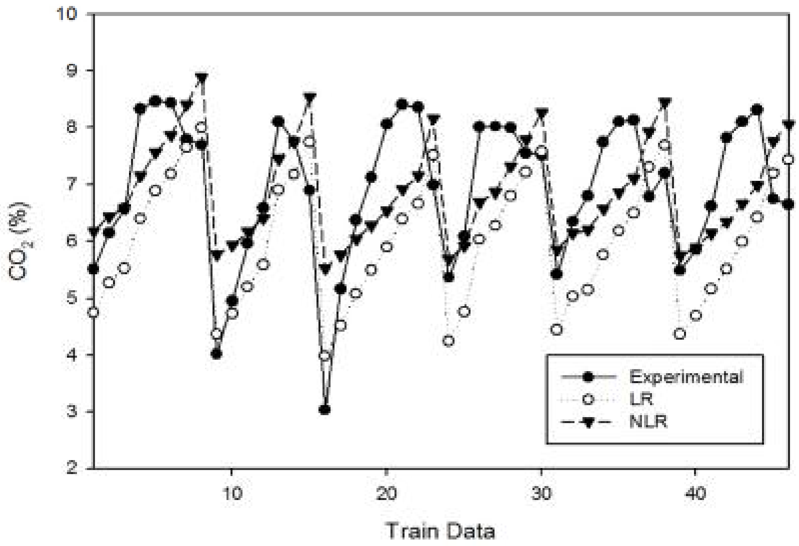


(a)

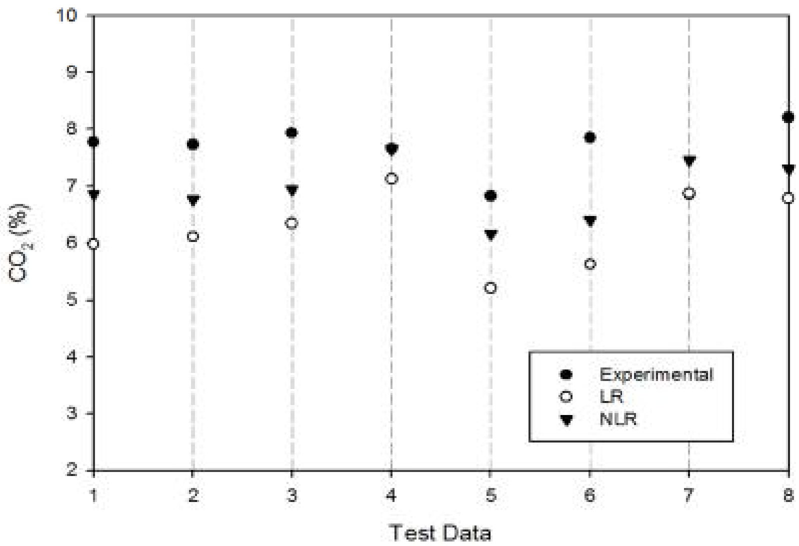


(b)

Figure 4.10. (a) Training (b) testing section of NO_x prediction with regression analysis for Model 2



(a)



(b)

Figure 4.11. (a) Training (b) testing section of CO_2 prediction with regression analysis for Model 2

The ANN architecture consisted of three main layers called as input, hidden and output layer (Figure 4.12). LMA was the best choice as learning algorithm for optimizing the weight to close the target values. Table 4.12 summarizes the details of ANN structure for each estimated engine-out parameters.

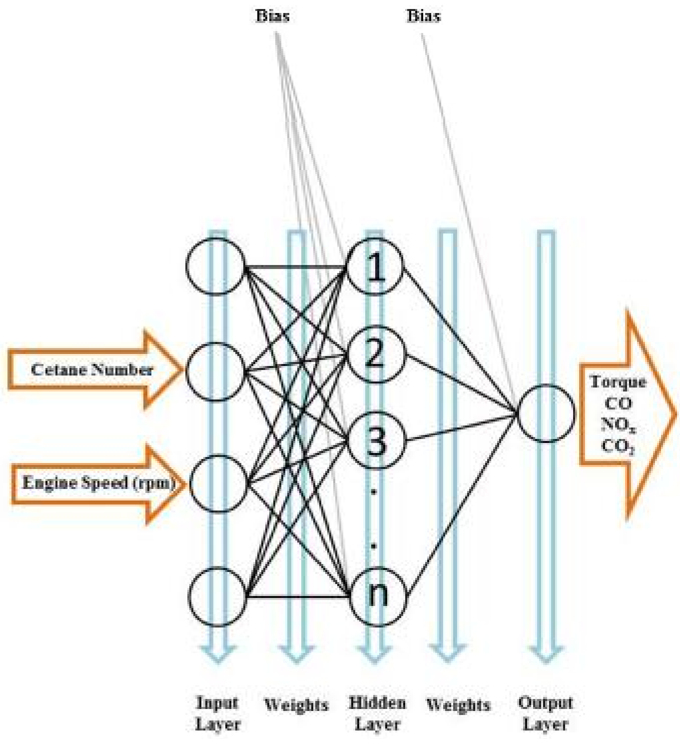


Figure 4.12. ANN structure in Model 2

Table 4.12. Details of ANN structure for Model 2

Estimated Parameter	Learning Algorithm	ANN Structure (2-n-1)	Hidden Layer Transfer Function	Output Layer Transfer Function
Torque	LM	2-16-1	logsig	purelin
CO	LM	2-30-1	logsig	purelin
NO_x	LM	2-21-1	logsig	purelin
CO_2	LM	2-19-1	logsig	purelin

Prediction equations for all engine-out parameters were given in Table 4.13. On the other hand, related weight and bias values can be seen from Table 4.14, 4.15, 4.16 and 4.17.

Table 4.13. Mathematical background behind ANN predictions for Model 2

$$Torque = 22.1618 * F_1 - 0.363 * F_2 + 6.4662 * F_3 - 36.0932 * F_4 + 33.292 * F_5 - 44.6394 * F_6 + 12.8081 * F_7 + 6.2020 * F_8 - 16.2669 * F_9 + 0.3339 * F_{10} + 60.4518 * F_{11} - 46.7053 * F_{12} - 53.5204 * F_{13} - 2.236 * F_{14} + 73.1915 * F_{15} + 178.7192 * F_{16} - 0.4437$$

$$CO = 5.216 * F_1 - 0.2 * F_2 + 45.7307 * F_3 + 100.04 * F_4 - 23.471 * F_5 + 46.1498 * F_6 - 14.7348 * F_7 + 55.5618 * F_8 + 5.3397 * F_9 - 139.4286 * F_{10} + 40.8178 * F_{11} - 198.6284 * F_{12} + 84.6714 * F_{13} + 26.8095 * F_{14} + 19.8464 * F_{15} - 75.4402 * F_{16} + 24.9286 * F_{17} - 17.9503 * F_{18} + 26.5 * F_{19} + 42.9 * F_{20} + 22.4511 * F_{21} + 14.3757 * F_{22} - 54.4685 * F_{23} + 23.9544 * F_{24} - 27.9286 * F_{25} + 76.4282 * F_{26} - 22.619 * F_{27} - 63.4101 * F_{28} - 54.8156 * F_{29} - 8{,}75 * F_{30} + 92.6076$$

$$NO_x = 181.3683 * F_1 + 35.6074 * F_2 + 7.06 * F_3 + 243.9065 * F_4 + 16.6831 * F_5 + 34.875 * F_6 + 192.8333 * F_7 + 268.8571 * F_8 + 277.5927 * F_9 + 243.5308 * F_{10} + 256.0091 * F_{11} - 7.8214 * F_{12} - 246.0534 * F_{13} + 601.731 * F_{14} - 6.7222 * F_{15} - 185.4974 * F_{16} - 126.6601 * F_{17} - 324.8259 * F_{18} - 116.25 * F_{19} - 48.7778 * F_{20} + 21.75 * F_{21} + 297.6792$$

$$CO_2 = 2.8191 * F_1 + 2.7036 * F_2 + 1.973 * F_3 - 0.2672 * F_4 + 0.5552 * F_5 - 1.4218 * F_6 - 0.9022 * F_7 - 0.0538 * F_8 - 0.0671 * F_9 + 1.3194 * F_{10} - 0.6479 * F_{11} + 1.4085 * F_{12} - 0.8709 * F_{13} + 1.5206 * F_{14} - 3.2995 * F_{15} - 0.6341 * F_{16} - 2.4499 * F_{17} - 1.4576 * F_{18} - 1.4486 * F_{19} + 2.5487$$

$$F_i = \frac{1}{1 + e^{-E_i}}$$

$$E_i = W_{1i} * (cetane\ number) + W_{2i} * (engine\ speed) + b_i$$

Table 4.14. Weight and bias values between input and hidden layer for torque prediction of Model 2

i	W_{1i}	W_{2i}	*i*	b_i
1	-2.86054	-9.32531	*1*	-75.2542
2	-15.3839	-3.50212	*2*	-61.749
3	4.212911	-0.32296	*3*	-34.4398
4	-49.7432	-4.6634	*4*	73.68683
5	-1.44055	82.14181	*5*	-72.7642
6	-29.2546	5.36743	*6*	62.40284
7	27.10033	-0.58334	*7*	1.382286
8	-73.3215	1.253154	*8*	62.3371
9	92.78635	-3.01421	*9*	-12.4961
10	-61.2714	1.238745	*10*	50.64481
11	-22.4856	0.449947	*11*	47.9927
12	-9.04126	-0.6873	*12*	8.922318
13	-15.8029	0.363507	*13*	-51.1667
14	-50.0837	1.25326	*14*	50.96558
15	13.65217	-0.19996	*15*	56.65958
16	0.012308	-0.00599	*16*	16.00715

Table 4.15. Weight and bias values between input and hidden layer for CO prediction of Model 2

i	W_{1i}	W_{2i}	*i*	b_i
1	-26.9167	36.07225	1	-89.043
2	2.523228	-0.50356	2	-5.32475
3	3.975675	74.99846	3	-72.9726
4	1.827833	2.163831	4	0.589161
5	1.107366	-14.7457	5	-94.7477
6	2.503242	-2.61318	6	46.00977
7	-59.3074	7.328965	7	-95.0362
8	5.106689	3.785576	8	46.80806
9	76.30285	1.795578	9	-94.196
10	141.5224	-2.05353	10	-84.0732
11	17.24242	0.10887	11	9.545465
12	-41.5846	-98.9424	12	8.915539
13	-111.545	1.94895	13	-82.9497
14	-22.2401	-2.35453	14	-43.3156
15	0.658875	0.192425	15	-65.5845
16	68.32794	-0.79281	16	-58.9996
17	458.856	-15.2097	17	-801.719
18	-12.9292	1.279268	18	45.71296
19	97.39844	-2.68503	19	56.88979
20	-68.2081	1.825778	20	-92.1161
21	-37.0683	41.62216	21	22.02962
22	62.33493	5458.765	22	35.22625
23	-48.832	-158.585	23	-25.6476
24	9.373054	1.175416	24	45.8314
25	159.4609	-4.76389	25	55.2035
26	21.03884	0.476049	26	-40.1893
27	14.20867	-4.77452	27	82.13312
28	2.706785	-0.22881	28	79.85047
29	-218.155	13.25756	29	66.87218
30	116.8765	-4.37981	30	53.22163

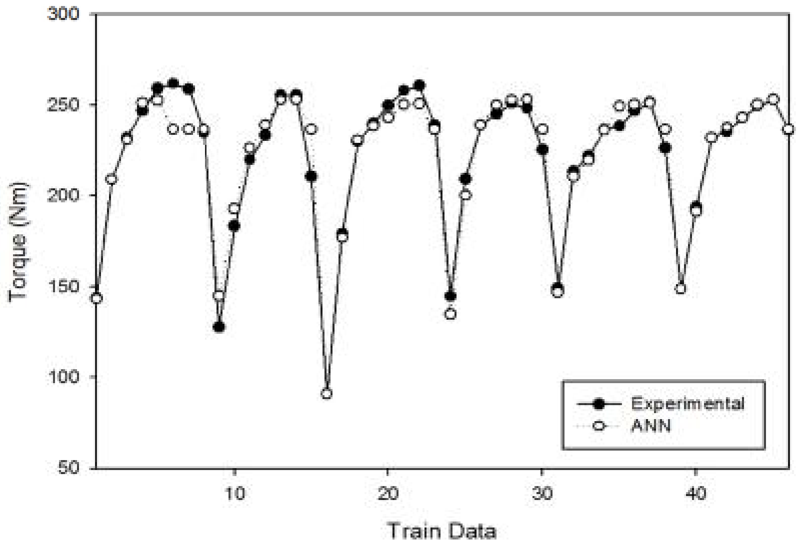
Table 4.16. Weight and bias values between input and hidden layer for NO_x prediction of Model 2

i	W_{1i}	W_{2i}	*i*	b_i
1	181.8093	-8.74283	*1*	16.24667
2	56.6175	1.853818	*2*	-89.1431
3	-56.2787	-0.93199	*3*	-17.3775
4	-22.5529	-0.7766	*4*	-68.2308
5	-82.6081	-1.7383	*5*	44.58272
6	-843.385	13.61811	*6*	-58.6527
7	101.2089	-1.66052	*7*	-60.4956
8	-1.61501	53.25291	*8*	-68.2462
9	48.85643	-1.16752	*9*	-26.2973
10	-136.523	1.550448	*10*	-64.2969
11	-17.8846	-32.083	*11*	-77.9375
12	-196.96	6.151304	*12*	53.86599
13	61.09747	-0.34962	*13*	-61.9517
14	116.2052	-0.36675	*14*	67.09083
15	-488.689	9.120713	*15*	43.98672
16	400.982	-9.78151	*16*	68.75443
17	-70.917	-0.29135	*17*	112.4102
18	-48.1974	0.522105	*18*	62.40461
19	-341.585	11.67151	*19*	57.74086
20	-211.017	4.766546	*20*	62.65218
21	-103.652	3.672796	*21*	17.30018

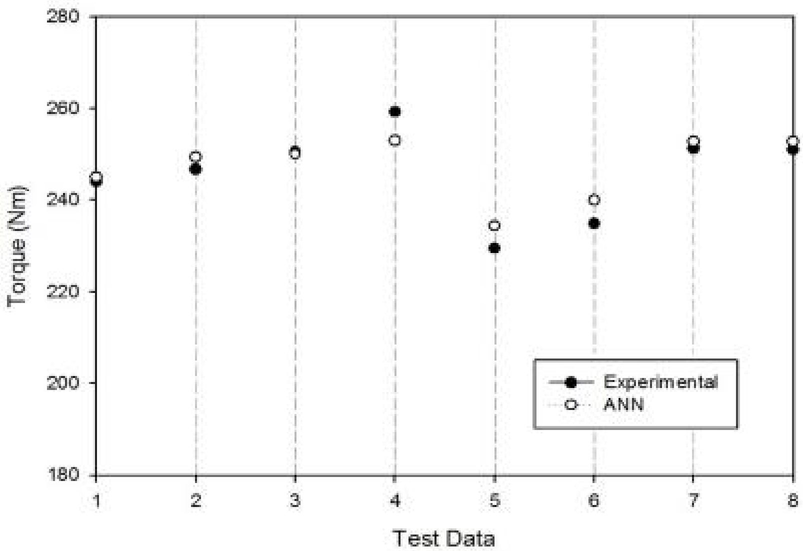
Table 4.17. Weight and bias values between input and hidden layer for CO_2 prediction of Model 2

i	W_{1i}	W_{2i}	*i*	b_i
1	1.16466	-0.02852	*1*	60.07156
2	-1.49101	0.015403	*2*	83.18655
3	-1.04013	0.041524	*3*	42.56363
4	0.909665	-0.05404	*4*	-44.2935
5	1.478063	-0.04	*5*	35.66466
6	-1.4722	0.063793	*6*	-15.3574
7	0.856268	0.011764	*7*	-74.174
8	-0.19672	0.006263	*8*	-64.5718
9	-0.055	0.017678	*9*	-61.1334
10	-1.07992	-0.01281	*10*	74.77333
11	0.421552	0.005182	*11*	-33.9001
12	0.553088	0.027897	*12*	-71.6313
13	1.14026	-0.03565	*13*	-47.256
14	1.042814	0.008967	*14*	-56.6051
15	1.186215	0.008676	*15*	-63.4713
16	0.224707	0.020449	*16*	-63.848
17	-1.53696	0.007988	*17*	63.71568
18	-1.2688	0.0078	*18*	28.53518
19	-0.64161	-0.01019	*19*	41.0182

Comparison of experimental and ANN predictions both for training and testing sections can easily be seen from the following Figure 4.13, 4.14, 4.15 and 4.16.

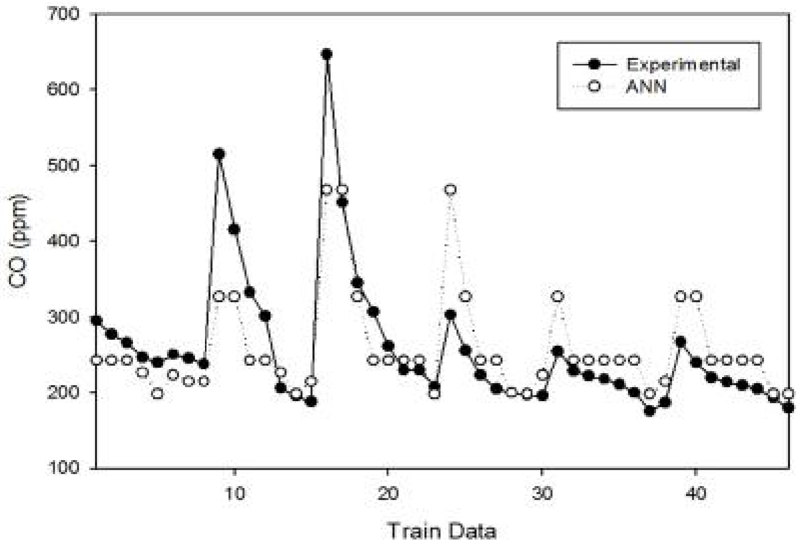


(a)

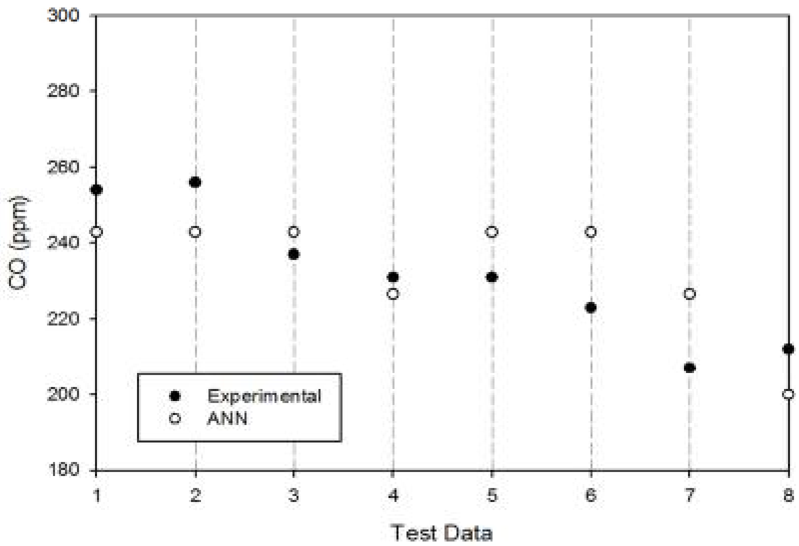


(b)

Figure 4.13. (a) Training (b) testing section of torque prediction with ANN for Model 2

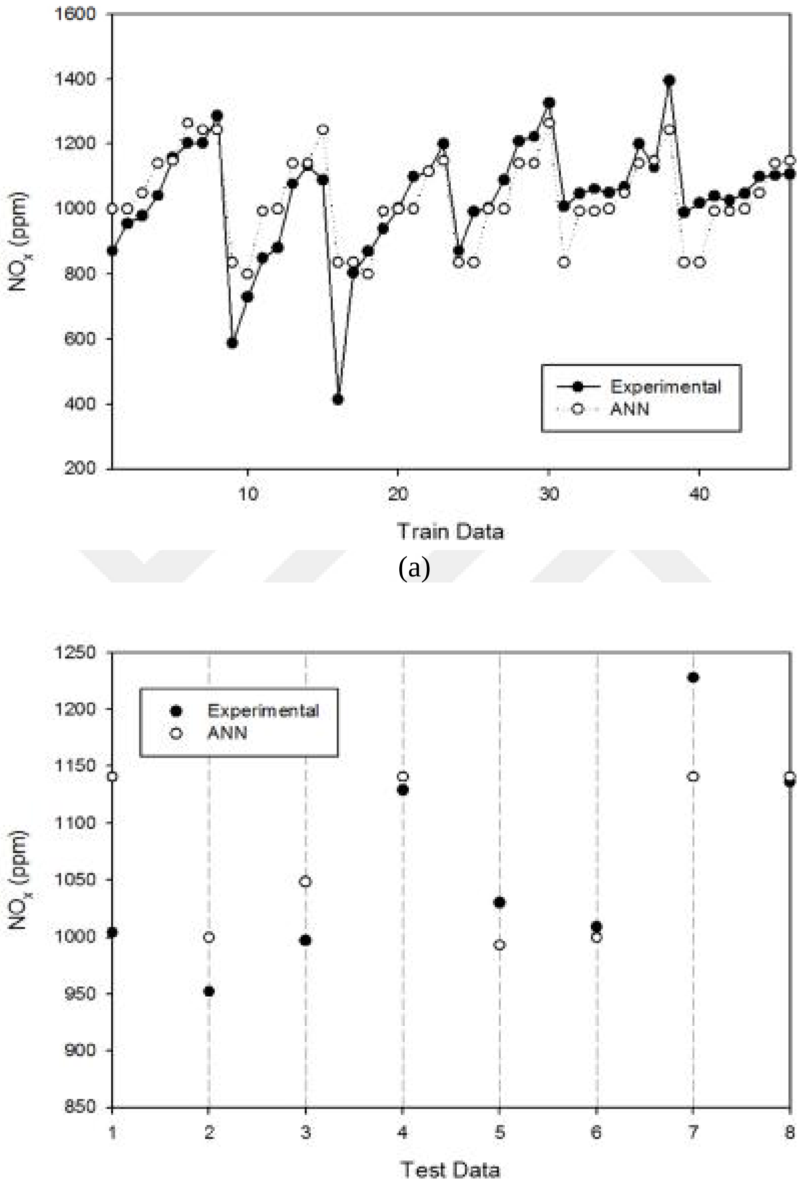


(a)



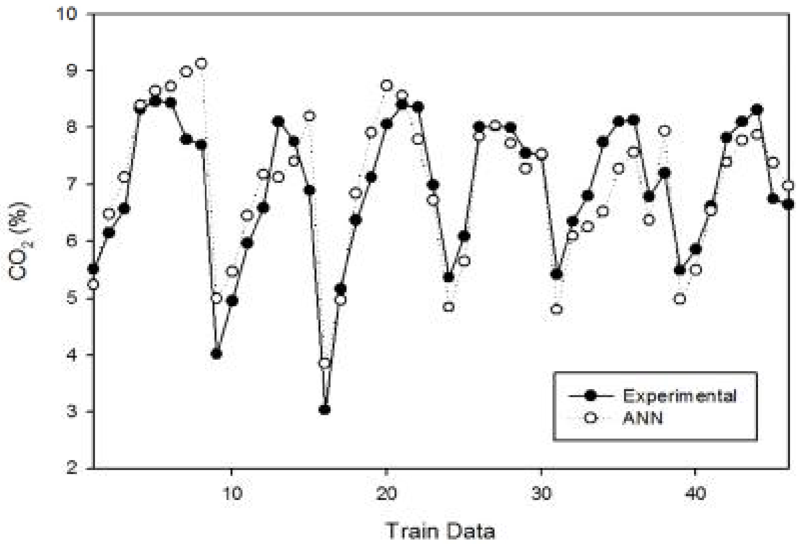
(b)

Figure 4.14. (a) Training (b) testing section of CO prediction with ANN for Model 2

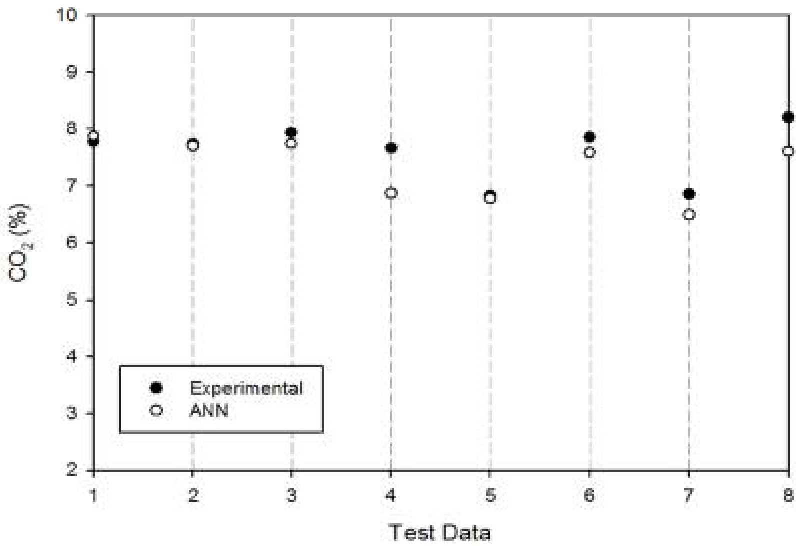


(b)

Figure 4.15. (a) Training (b) testing section of NO_x prediction with ANN for Model 2



(a)



(b)

Figure 4.16. (a) Training (b) testing section of CO_2 prediction with ANN for Model 2

An ANFIS structure consist of multilayer feed forward network which utilize neural network learning algorithm and fuzzy logic in order to set a relationship between input and output (Chang and Chang, 2006). ANFIS combines the advantages of both ANN and fuzzy logic and it gives effective and reliable results for estimations.

In ANFIS modelling, MATLAB software was used. Basic structure of ANFIS with two inputs and two fuzzy if-then rules was shown in Figure 3.11.

Determining the number of hidden layer neuron is one of the important issues in ANN modelling. Similarly, there is no definite rule to define number of membership functions. Therefore, it can be found by iterative process. But large number of membership functions is not recommended for time and computational load problems (Karimi et al., 2013).

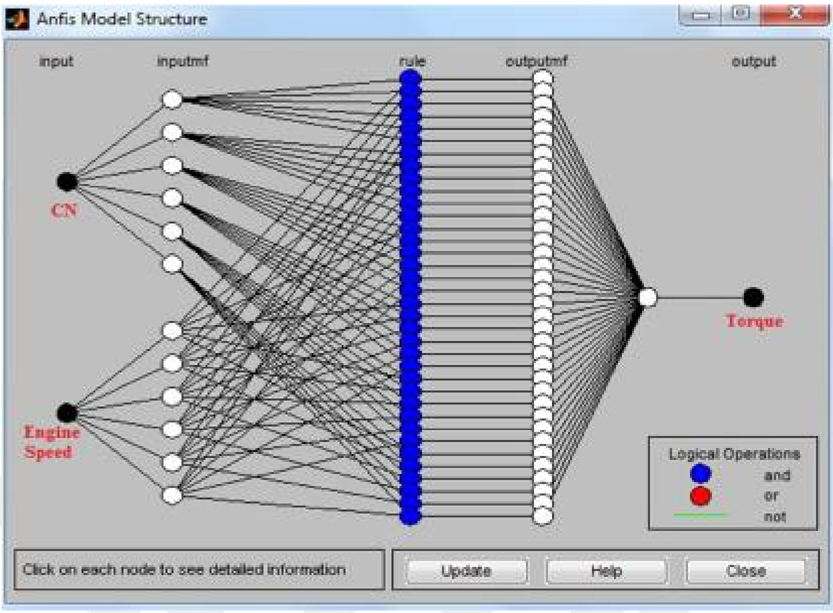
ANFIS uses gradient descent back-propagation neural networks to determine premise parameters. On the other hand, least square method is utilized for finding consequent parameters. This type of learning called as hybrid learning (Al-Hinti et al., 2009).

For ANFIS modelling the total data set is divided into two parts: training and testing as in other techniques. Table 4.18 shows the best ANFIS structures of Model 2 in order to obtain best prediction performance for each engine-out parameters. The best structures (number and type of membership functions) were set after some trial and errors and summarized in following table.

Table 4.18. Architectures of ANFIS models of Model 2

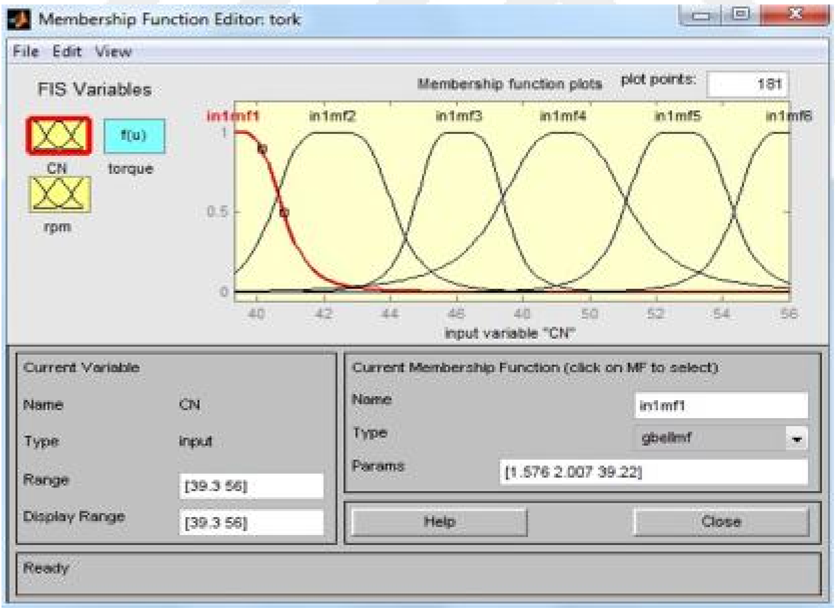
Estimated Parameter	Input			Output	FIS Generation	Optimization Method
	MF Number		MF Type	MF Type		
	Cetane Number	Engine Speed				
Torque	6	6	gbellmf	constant	grid partition	hybrid
CO	4	4	trimf	linear	grid partition	hybrid
NO_x	4	4	trimf	linear	grid partition	hybrid
CO_2	5	5	trimf	constant	grid partition	hybrid

Details of generated ANFIS architecture for torque, CO, NO_x and CO_2 predictions of Model 2 can be seen in following Figures 4.17, 4.19, 4.21 and 4.23. On the other hand, comparison of experimental and ANFIS predictions of engine-out parameters both for training and testing section can easily be seen from the following Figure 4.18, 4.20, 4.22 and 4.24.



Anfis Model Structure
input
inputmf
rule
outputmf
output
CN
Engine Speed
Torque
Logical Operations
and
or
not
Click on each node to see detailed information
Update
Help
Close

(a)



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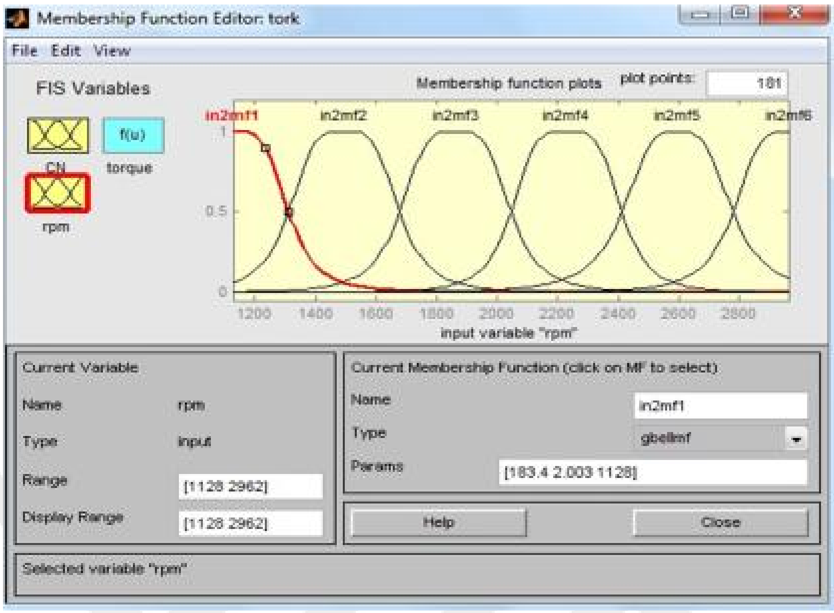
File Edit View
FIS Variables
CN
f(u)
torque
rpm
Membership function plots
plot points:
181
in1mf1
in1mf2
in1mf3
in1mf4
in1mf5
in1mf6
input variable "CN"
Current Variable
Name
CN
Type
input
Range
[39.3 56]
Display Range
[39.3 56]
Current Membership Function (click on MF to select)
Name
in1mf1
Type
gbellmf
Params
[1.576 2.007 39.22]
Help
Close
Ready

(b)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File Edit View
FIS Variables
CN
f(u)
torque
rpm
Membership function plots
plot points:
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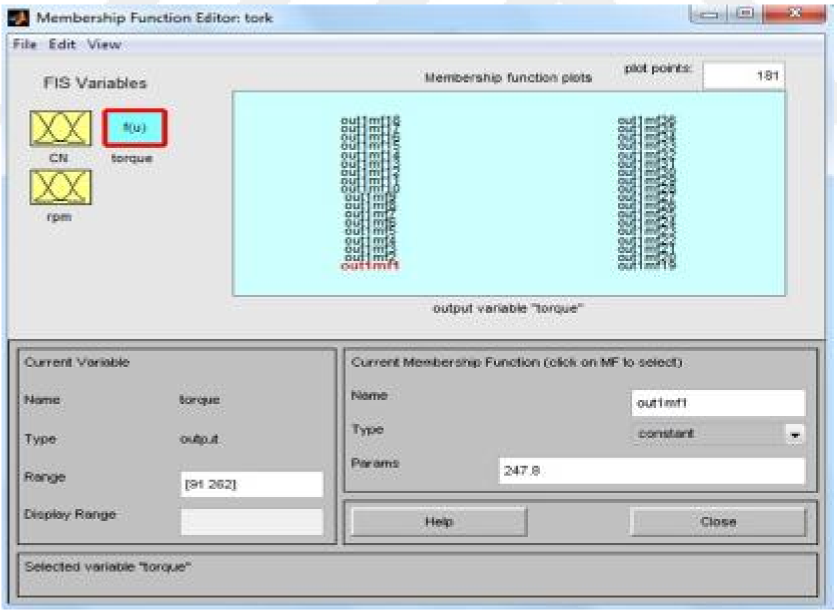
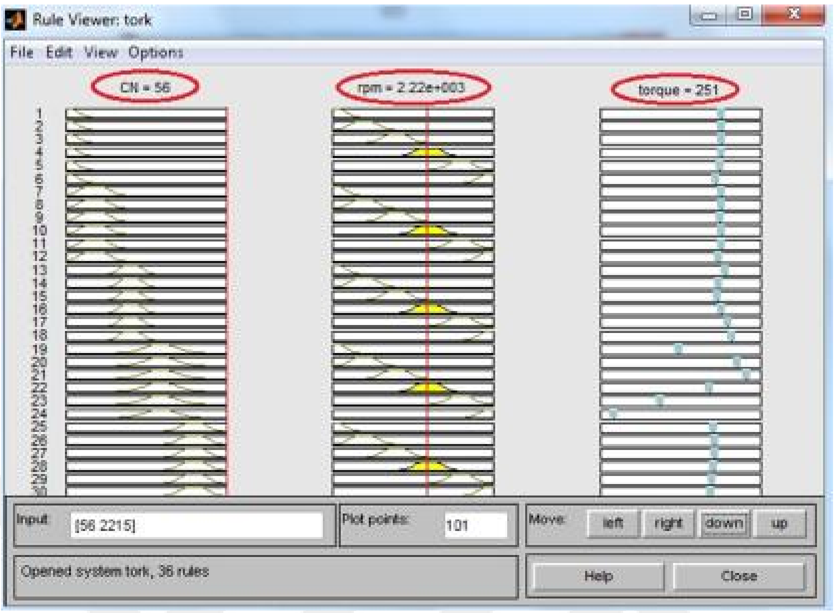
in2mf1
in2mf2
in2mf3
in2mf4
in2mf5
in2mf6
1
0.5
0
1200 1400 1600 1800 2000 2200 2400 2600 2800
input variable "rpm"
Current Variable
Name rpm
Type input
Range [1128 2962]
Display Range [1128 2962]
Current Membership Function (click on MF to select)
Name in2mf1
Type gbellmf
Params [183.4 2.003 1128]
Help
Close
Selected variable "rpm"

(c)

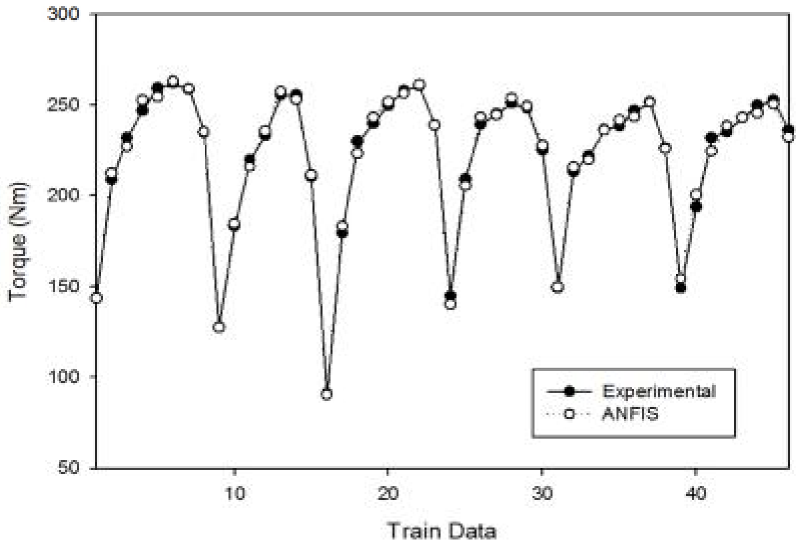

Membership Function Editor: tork
File Edit View
FIS Variables
CN
f(u)
torque
rpm
Membership function plots
plot points:
181
out1mf1
output variable "torque"
Current Variable
Name torque
Type output
Range [91 262]
Display Range
Current Membership Function (click on MF to select)
Name out1mf1
Type constant
Params 247.8
Help
Close
Selected variable "torque"

(d)

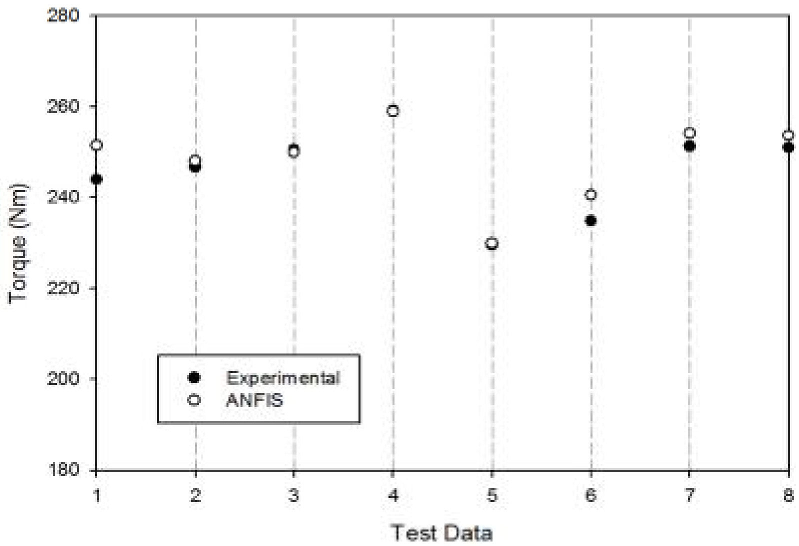


(e)

Figure 4.17. (a) ANFIS architecture (b) (c) membership functions of inputs (d) membership functions of output (e) fuzzy rules of torque prediction for Model 2

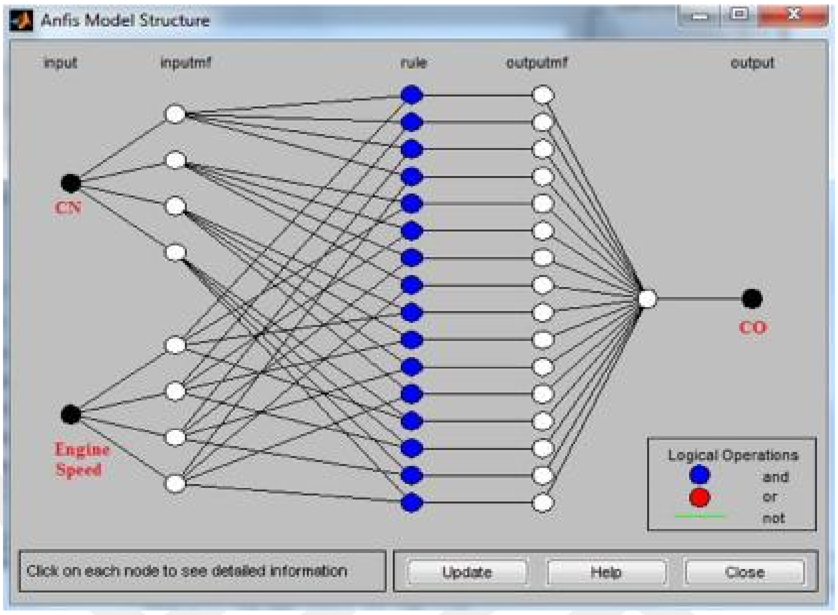


(a)



(b)

Figure 4.18 (a) Training (b) testing section of torque prediction with ANFIS for Model 2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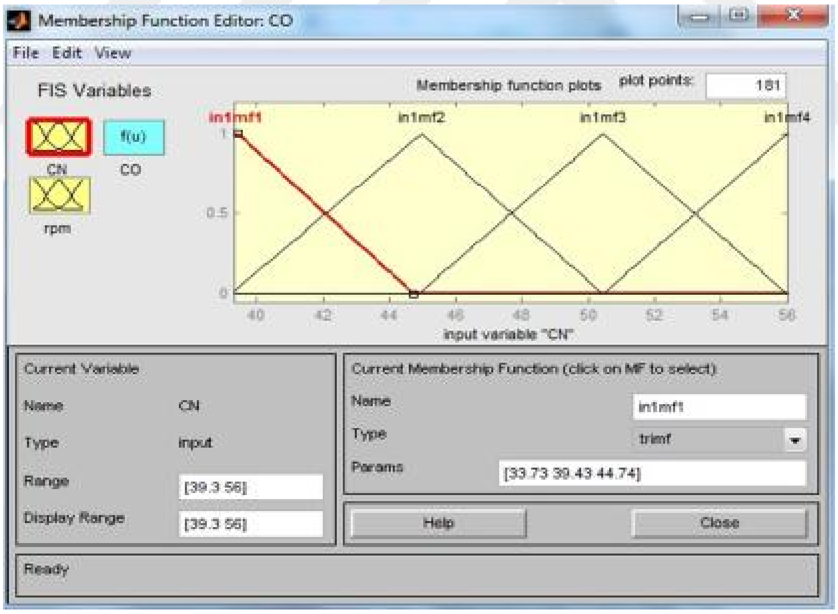
input
inputmf
rule
outputmf
output
CN
Engine Speed
CO
Logical Operations
and
or
not
Click on each node to see detailed information
Update
Help
Close

(a)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File Edit View
FIS Variables
CN
f(u)
CO
rpm
Membership function plots
plot points:
181
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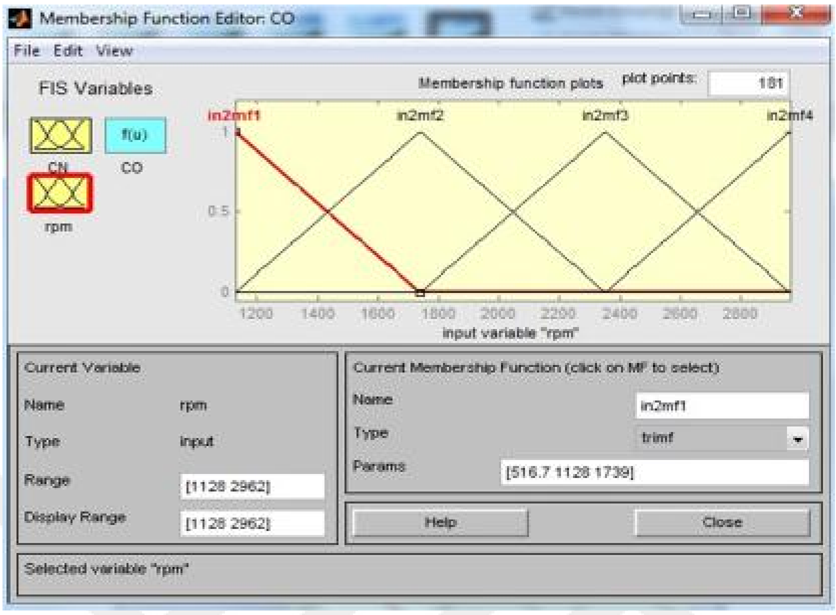
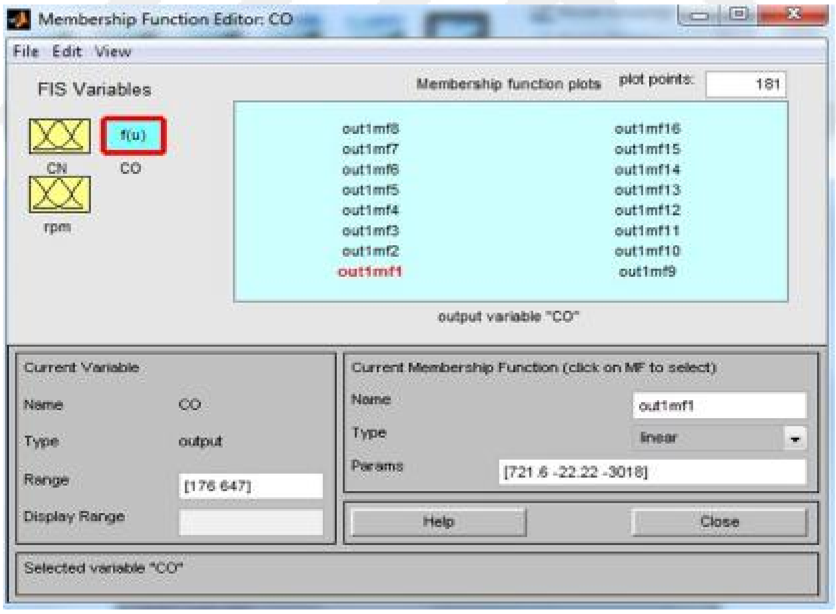
in1mf2
in1mf3
in1mf4
input variable "CN"
Current Variable
Name
CN
Type
input
Range
[39.3 56]
Display Range
[39.3 56]
Current Membership Function (click on MF to select)
Name
in1mf1
Type
trimf
Params
[33.73 39.43 44.74]
Help
Close
Ready

(b)


Membership Function Editor: CO
File Edit View
FIS Variables
Membership function plots
plot points: 181
in2mf1
in2mf2
in2mf3
in2mf4
CN
CO
f(u)
rpm
1200 1400 1600 1800 2000 2200 2400 2600 2800
input variable "rpm"
Current Variable
Name rpm
Type input
Range [1128 2962]
Display Range [1128 2962]
Current Membership Function (click on MF to select)
Name in2mf1
Type trimf
Params [516.7 1128 1739]
Help
Close
Selected variable "rpm"

(c)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File Edit View
FIS Variables
Membership function plots
plot points: 181
CN
CO
f(u)
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out1mf7 out1mf15
out1mf6 out1mf14
out1mf5 out1mf13
out1mf4 out1mf12
out1mf3 out1mf11
out1mf2 out1mf10
out1mf1 out1mf9
output variable "CO"
Current Variable
Name CO
Type output
Range [176 647]
Display Range
Current Membership Function (click on MF to select)
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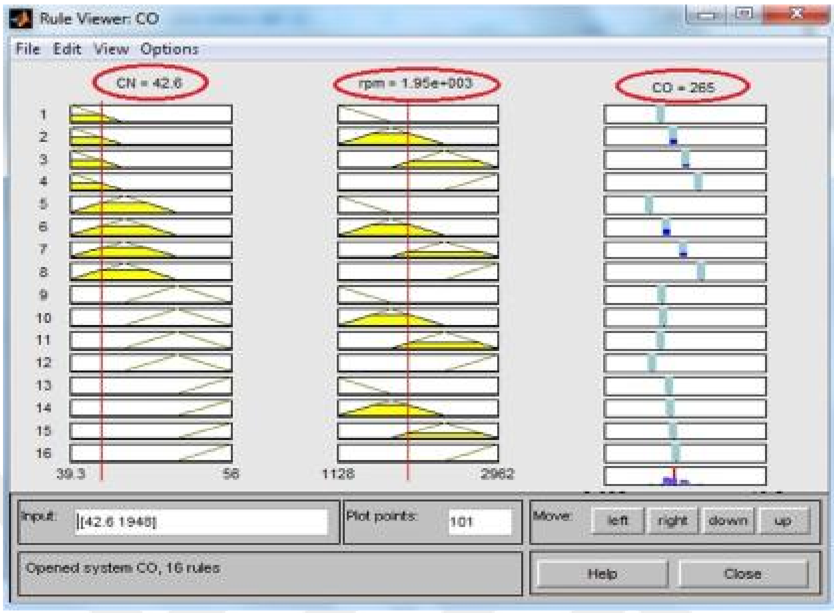
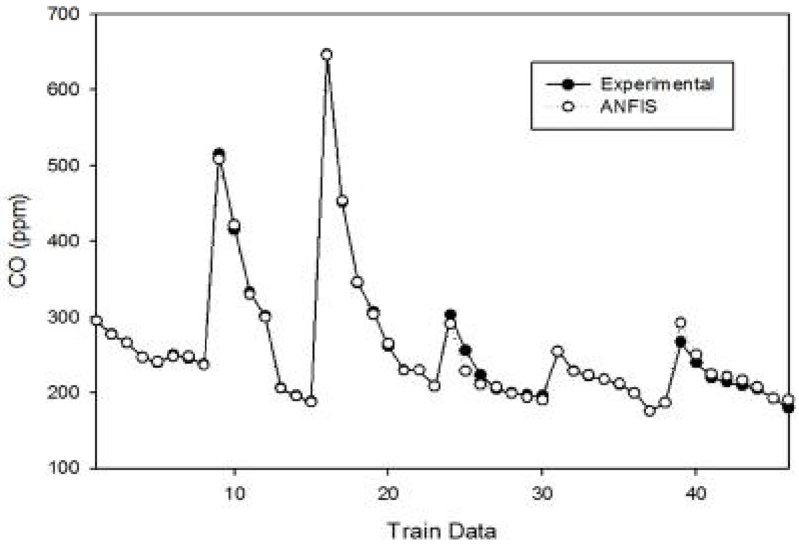
(d)

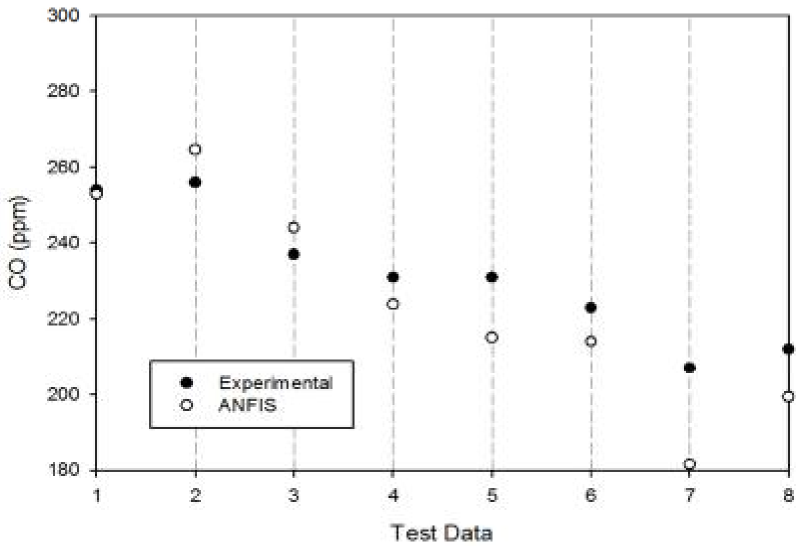


(e)

Figure 4.19. (a) ANFIS architecture (b) (c) membership functions of inputs (d) membership functions of output (e) fuzzy rules of CO prediction for Model 2

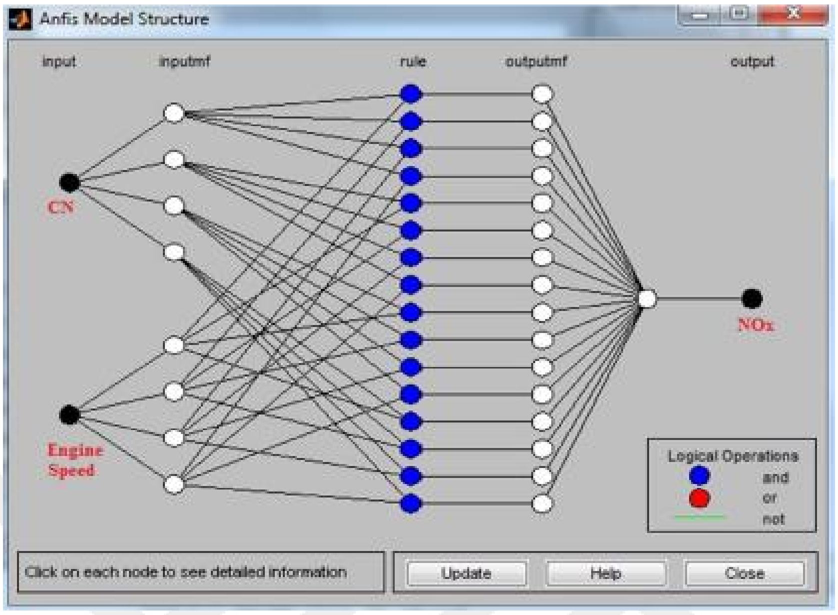


(a)

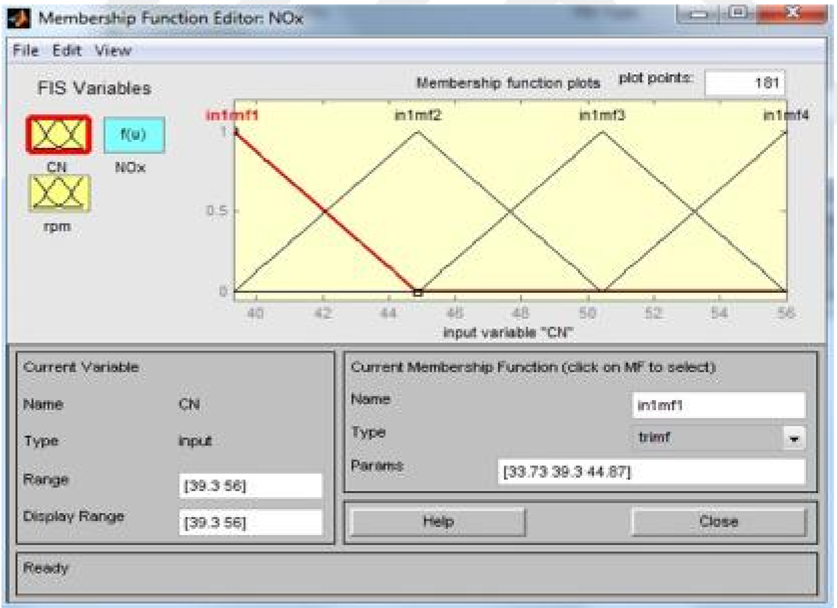


(b)

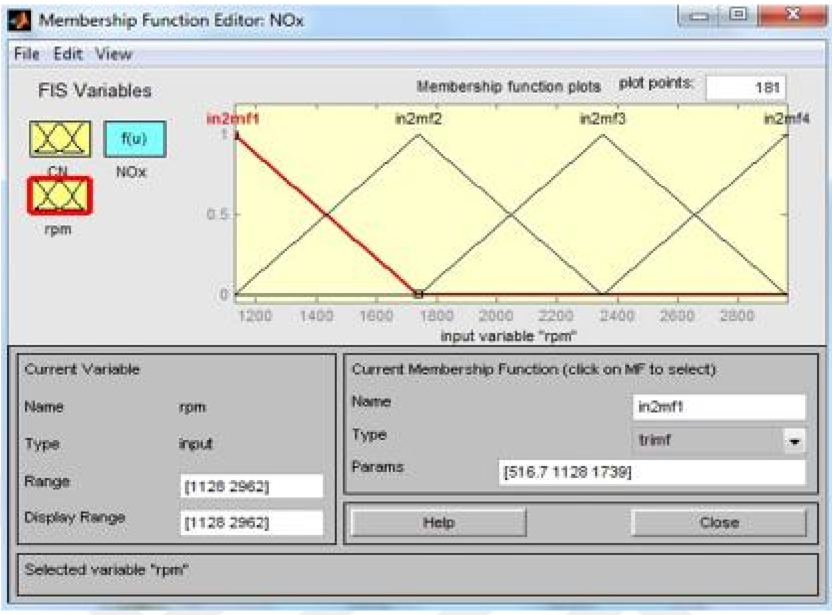
Figure 4.20. (a) Training (b) testing section of CO prediction with ANFIS for Model 2


Anfis Model Structure
input
inputmf
rule
outputmf
output
CN
Engine Speed
NOx
Logical Operations
and
or
not
Click on each node to see detailed information
Update
Help
Close

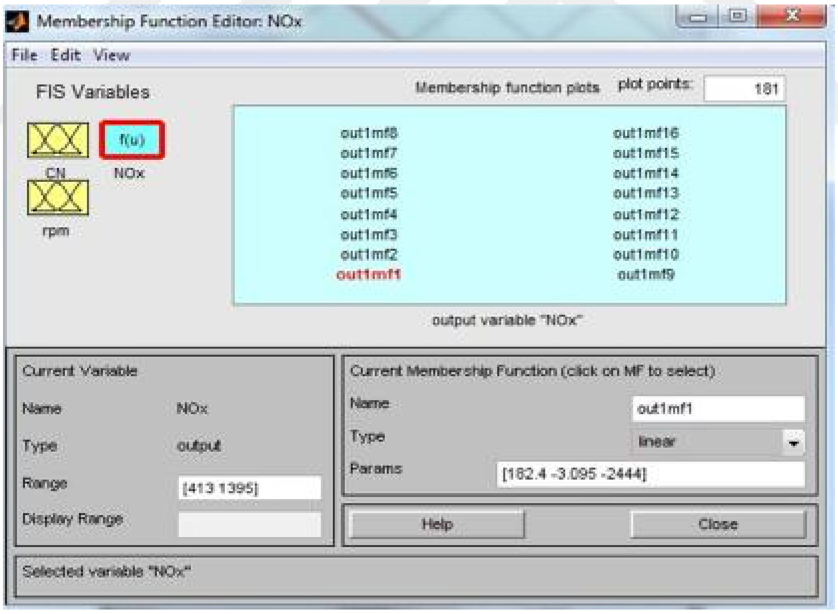
(a)


Membership Function Editor: NOx
File Edit View
FIS Variables
CN
f(u)
NOx
rpm
Membership function plots
plot points:
181
in1mf1
in1mf2
in1mf3
in1mf4
input variable "CN"
Current Variable
Name
CN
Type
input
Range
[39.3 56]
Display Range
[39.3 56]
Current Membership Function (click on MF to select)
Name
in1mf1
Type
trimf
Params
[33.73 39.3 44.87]
Help
Close
Ready

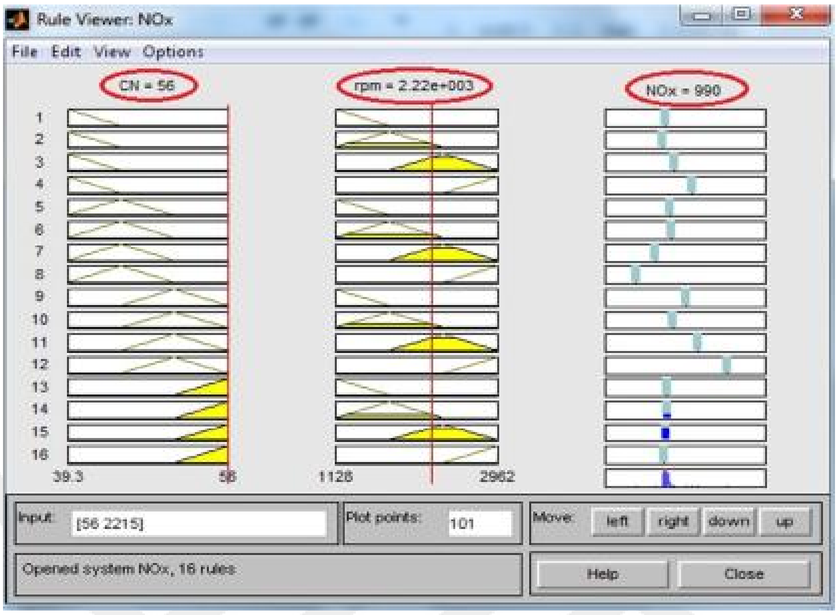
(b)


Membership Function Editor: NOx
File Edit View
FIS Variables
CN
f(u)
NOx
rpm
Membership function plots
plot points:
181
in2mf1
in2mf2
in2mf3
in2mf4
input variable "rpm"
Current Variable
Name rpm
Type input
Range [1128 2962]
Display Range [1128 2962]
Current Membership Function (click on MF to select)
Name in2mf1
Type trimf
Params [516.7 1128 1739]
Help
Close
Selected variable "rpm"

(c)

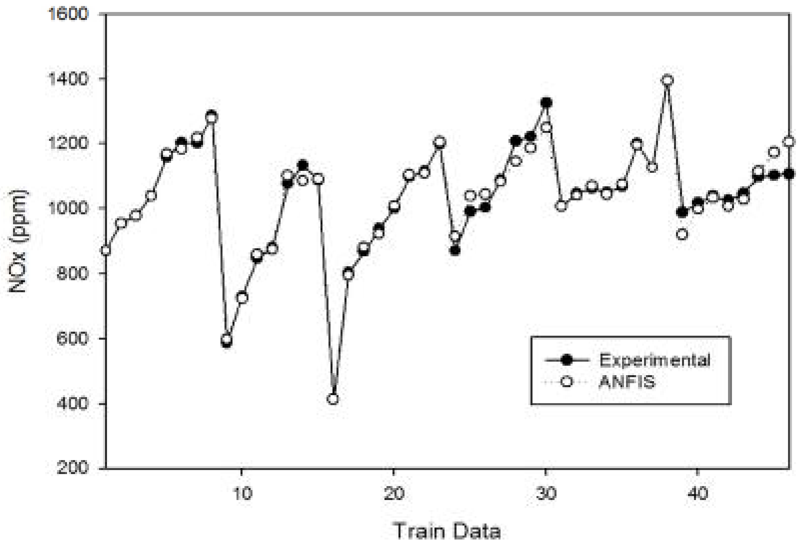

Membership Function Editor: NOx
File Edit View
FIS Variables
CN
f(u)
NOx
rpm
Membership function plots
plot points:
181
out1mf8 out1mf16
out1mf7 out1mf15
out1mf6 out1mf14
out1mf5 out1mf13
out1mf4 out1mf12
out1mf3 out1mf11
out1mf2 out1mf10
out1mf1 out1mf9
output variable "NOx"
Current Variable
Name NOx
Type output
Range [413 1395]
Display Range
Current Membership Function (click on MF to select)
Name out1mf1
Type linear
Params [182.4 -3.095 -2444]
Help
Close
Selected variable "NOx"

(d)

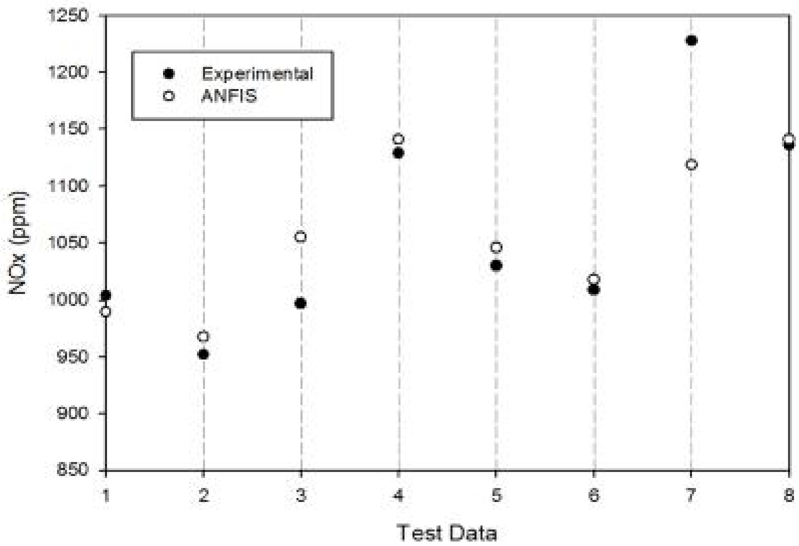


(e)

Figure 4.21. (a) ANFIS architecture (b) (c) membership functions of inputs (d) membership functions of output (e) fuzzy rules of NO_x prediction for Model 2

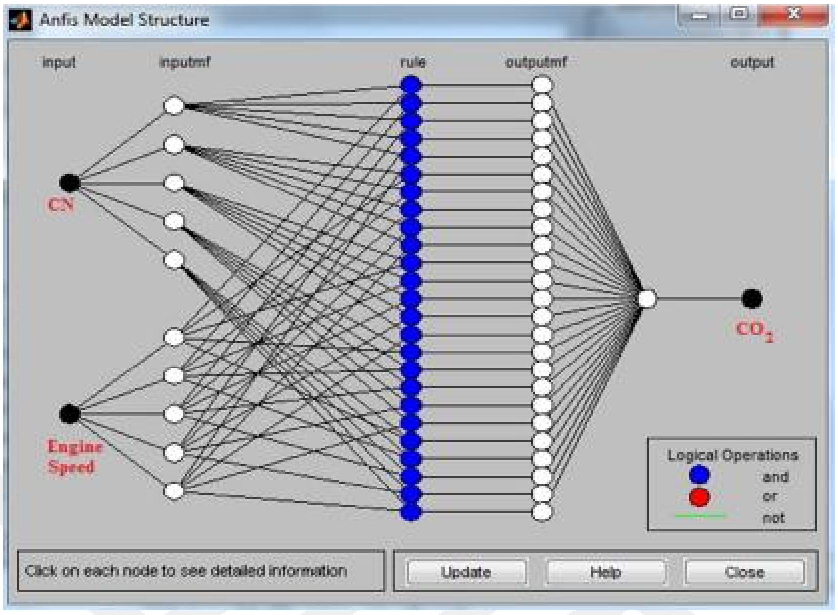


(a)

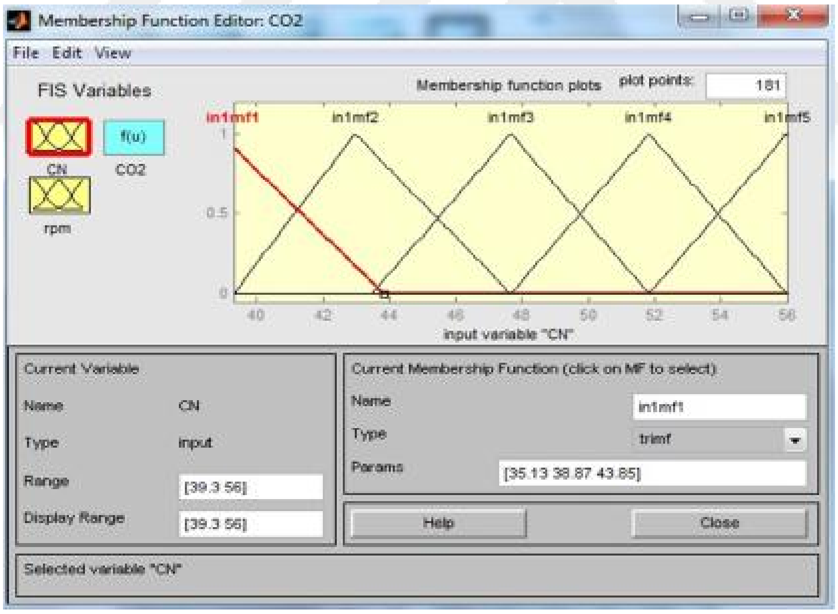


(b)

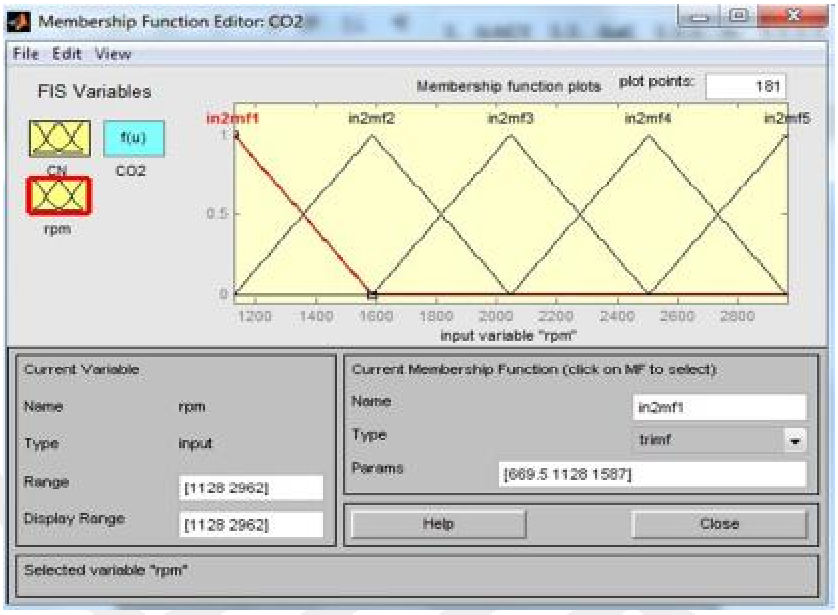
Figure 4.22. (a) Training (b) testing section of NO_x prediction with ANFIS for Model 2


Anfis Model Structure
input
inputmf
rule
outputmf
output
CN
Engine Speed
CO_2
Logical Operations
and
or
not
Click on each node to see detailed information
Update
Help
Close

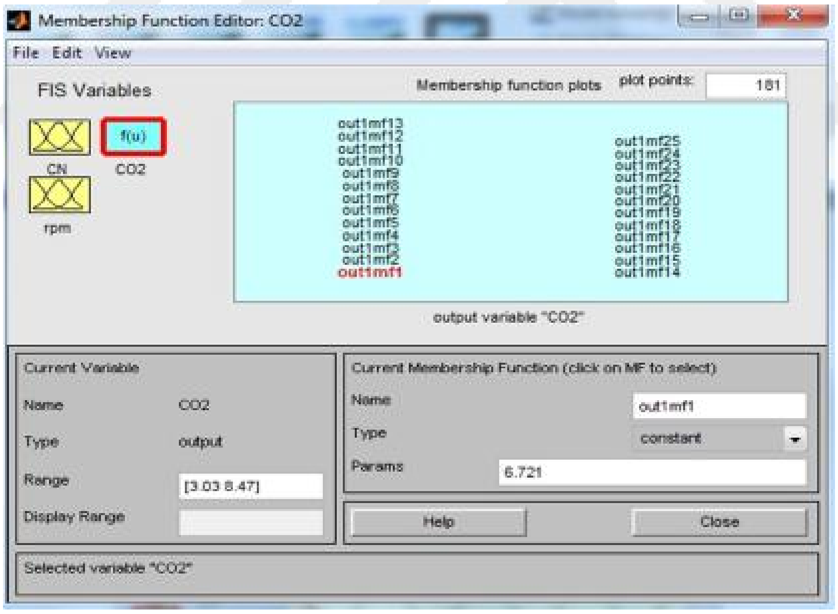
(a)


Membership Function Editor: CO2
File Edit View
FIS Variables
CN
f(u)
CO2
rpm
Membership function plots
plot points:
181
in1mf1
in1mf2
in1mf3
in1mf4
in1mf5
input variable "CN"
Current Variable
Name
CN
Type
input
Range
[39.3 56]
Display Range
[39.3 56]
Current Membership Function (click on MF to select)
Name
in1mf1
Type
trimf
Params
[35.13 38.87 43.85]
Help
Close
Selected variable "CN"

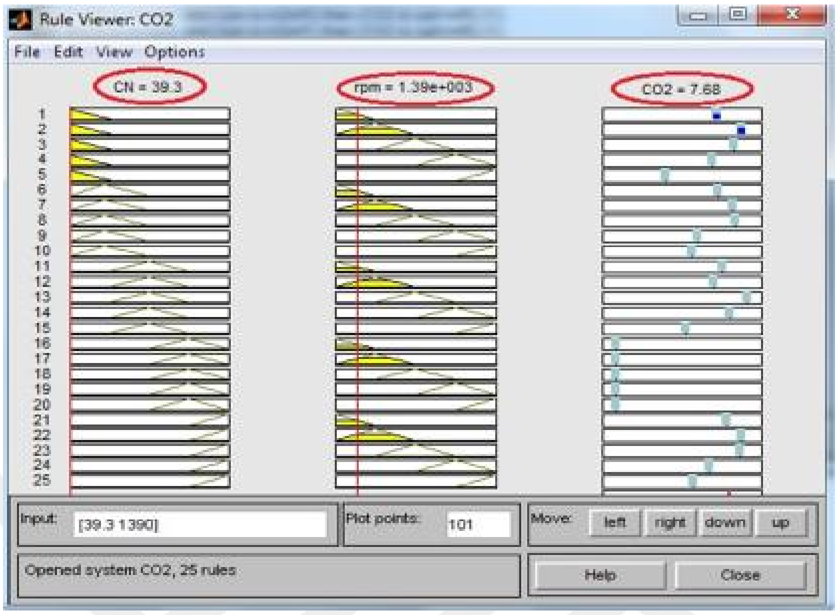
(b)


Membership Function Editor: CO2
File Edit View
FIS Variables
Membership function plots
plot points:
181
CN
CO2
rpm
f(u)
in2mf1
in2mf2
in2mf3
in2mf4
in2mf5
input variable "rpm"
Current Variable
Name rpm
Type input
Range [1128 2962]
Display Range [1128 2962]
Current Membership Function (click on MF to select)
Name in2mf1
Type trimf
Params [669.5 1128 1587]
Help
Close
Selected variable "rpm"

(c)

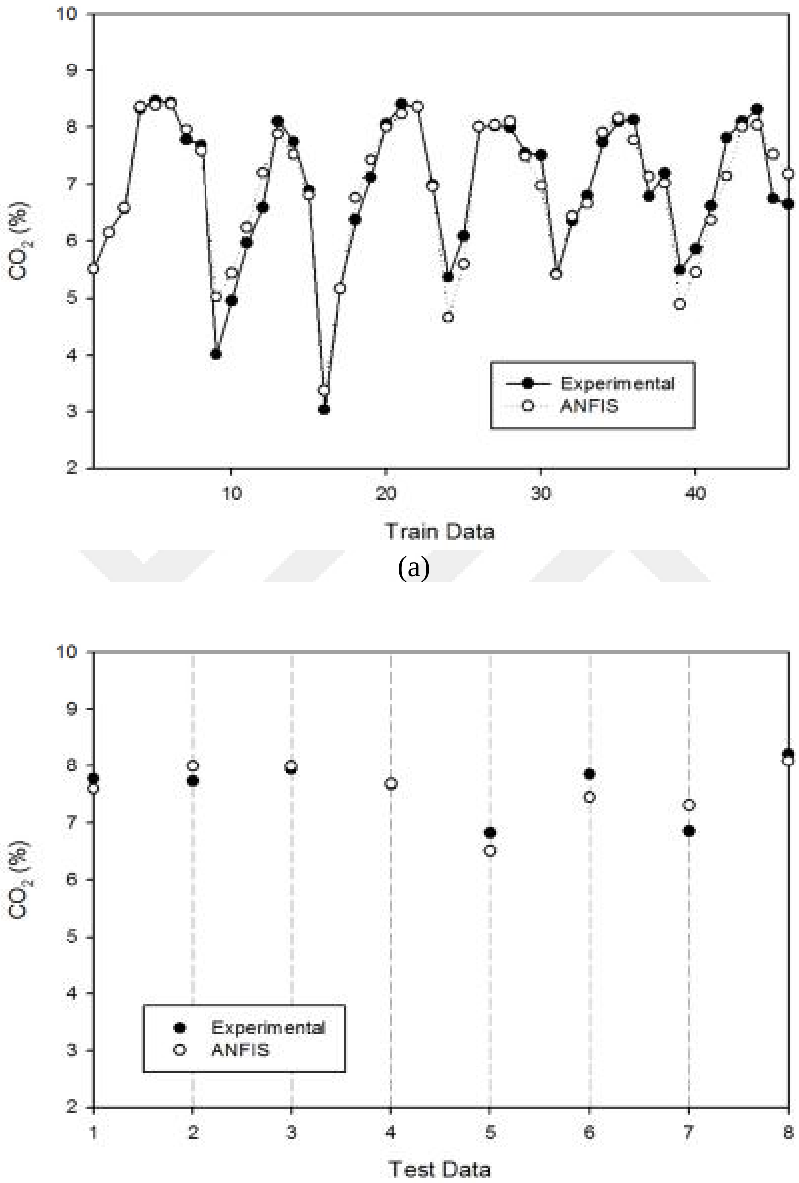

Membership Function Editor: CO2
File Edit View
FIS Variables
Membership function plots
plot points:
181
CN
CO2
rpm
f(u)
output variable "CO2"
Current Variable
Name CO2
Type output
Range [3.03 8.47]
Display Range
Current Membership Function (click on MF to select)
Name out1mf1
Type constant
Params 6.721
Help
Close
Selected variable "CO2"

(d)



(e)

Figure 4.23. (a) ANFIS architecture (b) (c) membership functions of inputs (d) membership functions of output (e) fuzzy rules of CO_2 prediction for Model 2



(a)

(b)

Figure 4.24. (a) Training (b) testing section of CO_2 prediction with ANFIS for Model 2

Table 4.19. Prediction performance evaluation for Model 2

Estimated Parameter	***Method***	***MAPE (%)***	
		Training	***Testing***
Torque	LR	11.81	6
	NLR	14.01	8.39
	ANN	2.49	1.22
	ANFIS	1.17	1.09
CO	LR	16.19	9.41
	NLR	14.94	9.16
	ANN	14.82	5.39
	ANFIS	1.5	4.89
NO_x	LR	8.87	5.65
	NLR	9.84	5.59
	ANN	9.58	4.6
	ANFIS	1.82	2.72
CO_2	LR	16.61	17.6
	NLR	13.33	10.63
	ANN	7.86	3.91
	ANFIS	4.12	3.1

The summary of above figures of Model 2 can be found in Table 4.19. In previous Model 1, the prediction performance of ANN was better than linear regression. Performance of ANN is also superior according to both linear and non-linear regression analysis in Model 2. Besides that, ANFIS approach which combines advantages of neural networks and fuzzy logic provided best performance for engine-out parameters estimations. It means that predictions can be achieved with less error by using ANFIS. According to Table 4.19, ANN and ANFIS gave satisfactory results.

4.3. Prediction of Operational Parameters of a Direct Injection Turbocharged Spark Ignition Engine Operated with Gasoline (Model 3)

In Model 3, various operational engine parameters; duration of injection, specific fuel consumption and exhaust gas temperature at turbine inlet (DOI, SFC, T_{exh}) predictions were achieved. The experiments were conducted on a direct injection spark ignition engine operated with gasoline (95 RON) in Istituto Motori-CNR, Napoli. Engine specifications and schematic view of test rig can be seen from Table 4.20 and Figure 4.25, respectively.

Table 4.20. Engine specifications in Model 3 (Tosun et al., 2017)

Displacement	1368 cm^3
Number of cylinders	4
Bore/stroke	72/84 mm
Compression ratio	10:1
Valves per cylinder	2 for intake, 2 for exhaust
Valves timing	Variable through camshaft phasing on the intake and exhaust side
Intake system	Turbocharging with up to 1,49 bar gauge pressure
Fuel system	Wall guided DI at 100 bar, 6 holes nozzle

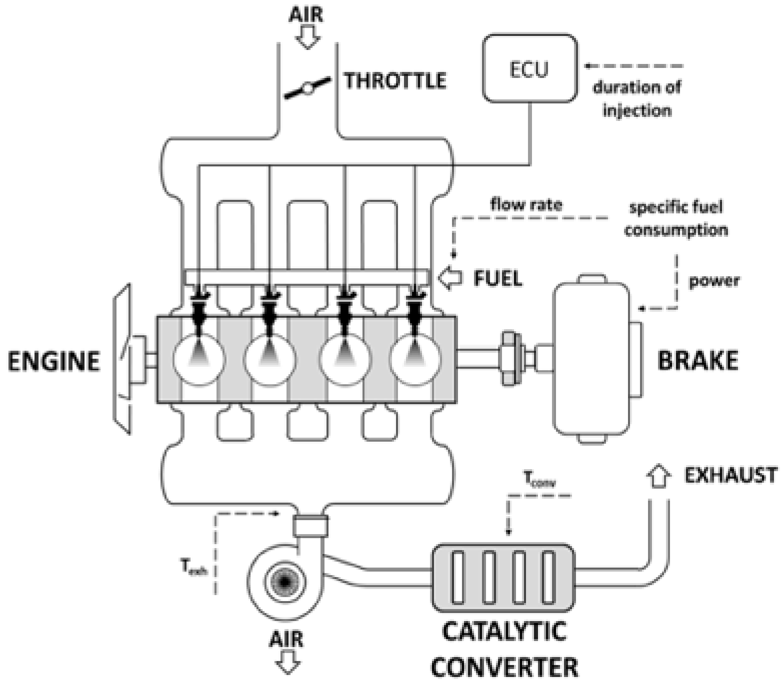


Figure 4.25. Schematic view of test rig in Model 3 (Tosun et al., 2017)

Load and engine speed (rpm) are very important and fundamental parameters in order to obtain engine power that drives vehicle. The values of them can easily be correlated with crank shaft and throttle positioning sensor values. Therefore, these two essential parameters were chosen as input for estimation models. DOI, SFC and T_{exh} were selected for estimation parameters. DOI shows generally linear correlation with load. Prediction of trend of this parameter will be beneficial for feed-forward and purposes of diagnostic. SFC is another important and fundamental parameter for implementation of multi-objective optimization. Therefore, it was chosen as predicted parameter. T_{exh} requires to be kept under certain limits in order to prevent the turbine overheating. Therefore, the prediction of T_{exh} parameter against engine speed-load curve should be useful for safety purpose.

Engine speed was changed between 1000 and 5500 rpm with BMEP value up to 22 bar as load parameter. Spark timing setting map towards engine speed and load (bmep) can be seen from Figure 4.26.

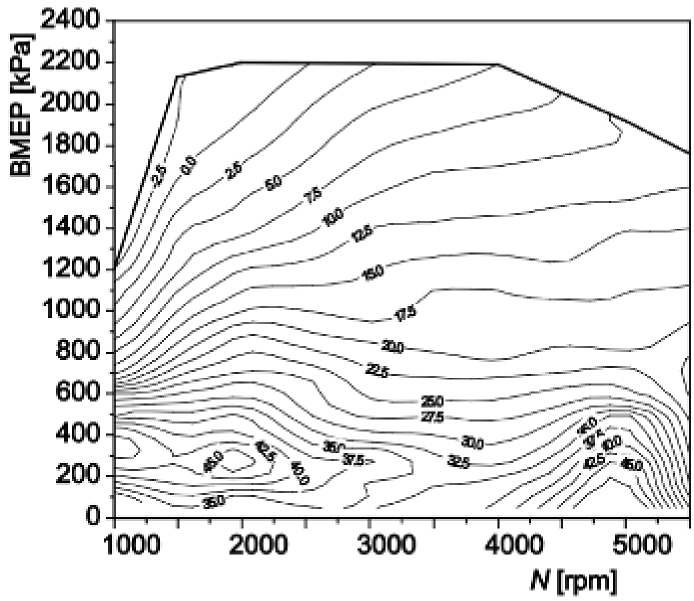


Figure 4.26. Spark timing setting map (Tosun et al., 2017)

By using experimental results, the total data set was divided into two groups: training and testing as in previous models. The ratio of training data to testing data is about 4.7 for each estimated parameters. Testing data was randomly selected from the total data set. DOI, SFC and T_{exh} were estimated parameters whereas engine speed (X_1) and BMEP (X_2) were input parameters.

Table 4.21 shows the regression coefficients of linear and non-linear regression equations. Following Figure 4.27, 4.28 and 4.29 demonstrate the graphical representation of actual (experimental) and regression results.

Table 4.21. Linear and non-linear regression results of Model 3

$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$ $X_1: engine\ speed,\ X_2: bmep$			
$\boldsymbol{y}$	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$
DOI *(ms)*	0.486	0.0000218	0.002
SFC *($gkW^{-1}h^{-1}$)*	401.738	0.003	-0.101
T_{exh} *(^oC)*	355.152	0.078	0.181
$y = \alpha_0 (X_1{}^{\alpha_1})(X_2{}^{\alpha_2})$ $X_1: engine\ speed,\ X_2: bmep$			
$\boldsymbol{y}$	$\boldsymbol{\alpha_0}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\alpha_2}$
DOI *(ms)*	0.02851	-0.041	0.709
SFC *($gkW^{-1}h^{-1}$)*	990.8319	0.064	-0.26
T_{exh} *(^oC)*	18.4502	0.289	0.212

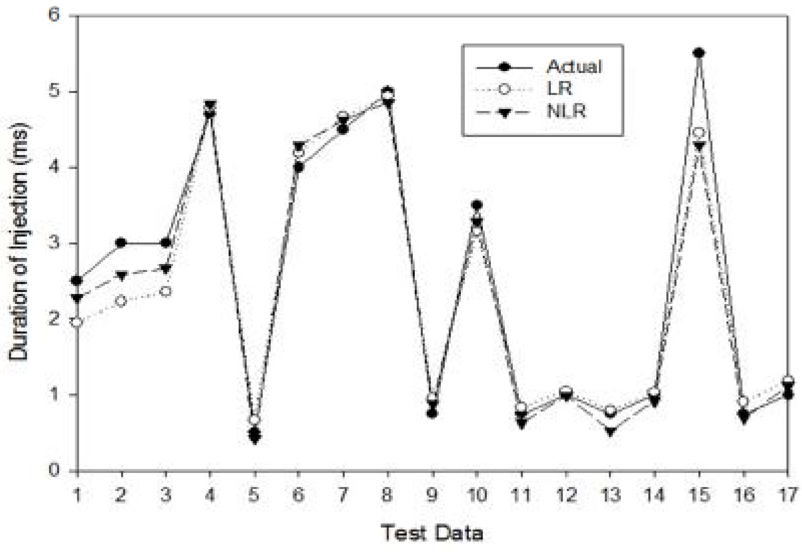


Figure 4.27. Testing section of DOI prediction with regression analysis for Model 3

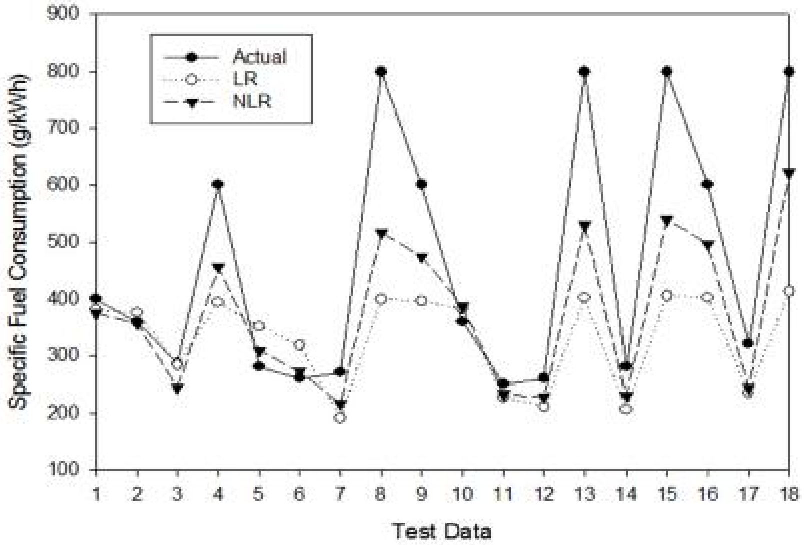


Figure 4.28.Testing section of SFC prediction with regression analysis for Model 3

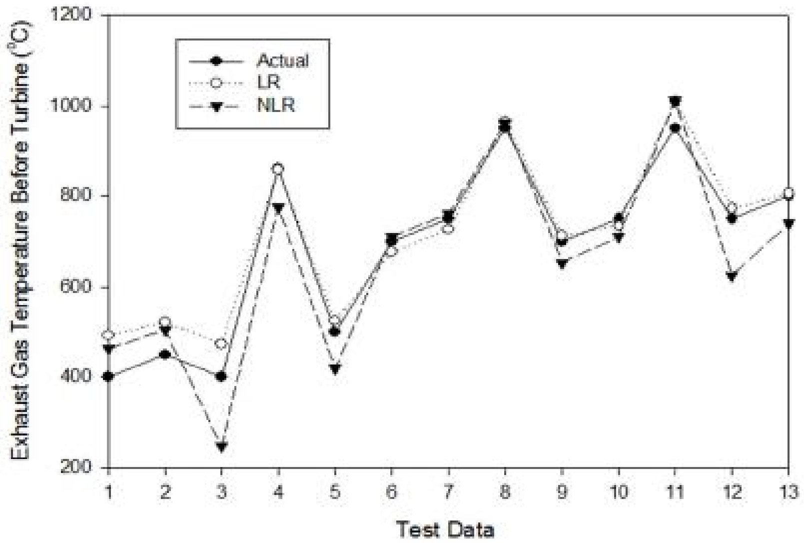


Figure 4.29. Testing section of T_{exh} prediction with regression analysis for Model 3

Prediction capabilities of both LR and NLR are nearly same according to above figures. Especially, SFC results are very bad in regression analysis; because of this parameter is a result of various complex interactions such as friction, pumping, losses of combustion etc. Therefore, assuming a correlation like LR or NLR have less chance to predict results since SFC must be represented and correlated with much more parameters except engine speed and load.

The ANN structure (Figure 4.30) consisted of three main layers called as input, hidden and output layer and LMA was selected as learning algorithm for optimizing the weight to close the target values as in previous models. Table 4.22 summarizes the details of ANN structure for each estimated engine-out parameters.

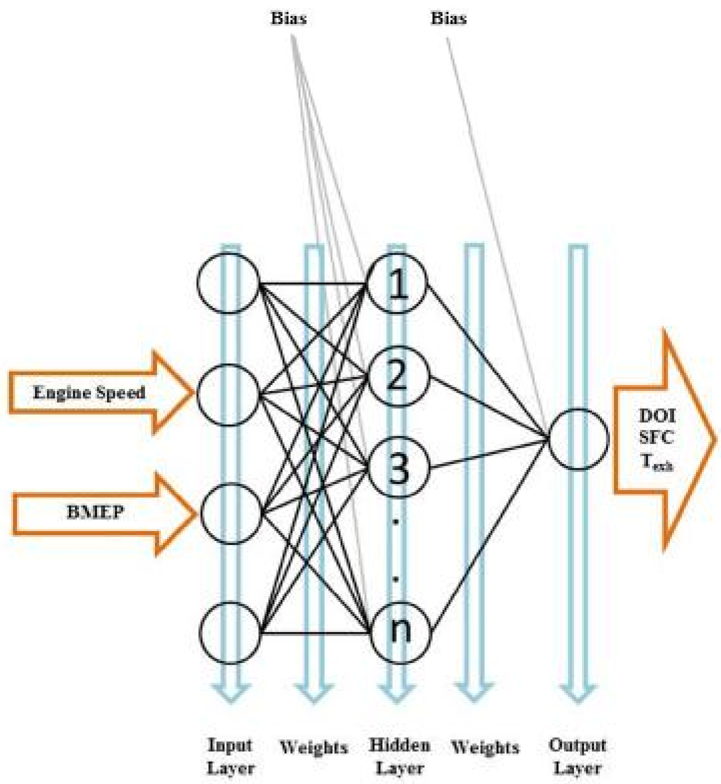


Figure 4.30.ANN structure in Model 3

Table 4.22. Details of ANN structure for Model 3

Estimated Parameter	Learning Algorithm	ANN Structure (2-n-1)	Hidden Layer Transfer Function	Output Layer Transfer Function
DOI	LM	2-5-1	logsig	purelin
SFC	LM	2-3-1	logsig	purelin
T_{exh}	LM	2-7-1	logsig	purelin

Prediction equations for all operational parameters were given in Table 4.23. On the other hand, related weight and bias values can be seen from Table 4.24, 4.25 and 4.26.

Table 4.23. Mathematical background behind ANN predictions for Model 3

$$DOI = 0.353968 * F_1 + 2.172024 * F_2 + 0.68372 * F_3 - 2.0028 * F_4 - 1.06189 * F_5 + 3.419145$$

$$SFC = 7422.849 * F_1 - 22.4132 * F_2 + 8.647945 * F_3 + 283.864$$

$$T_{exh} = 25.60757 * F_1 + 922.8861 * F_2 + 71.43501 * F_3 + 81.66653 * F_4 - 2.57144 * F_5 - 13.5695 * F_6 - 47.5116 * F_7 + 61.76924$$

$$F_i = \frac{1}{1 + e^{-E_i}}$$

$$E_i = W_{1i} * (engine\ speed) + W_{2i} * (bmep) + b_i$$

Table 4.24. Weight and bias values between input and hidden layer for DOI prediction of Model 3

i	W_{1i}	W_{2i}	*i*	b_i
1	-1.1603	1.878318	1	-17.3055
2	-6.82e-6	0.00509	2	-2.177
3	-0.01872	0.093073	3	-50.6196
4	-0.00179	-0.00611	4	18.02975
5	0.006188	-0.01287	5	10.75479

Table 4.25. Weight and bias values between input and hidden layer for SFC prediction of Model 3

i	W_{1i}	W_{2i}	*i*	b_i
1	1.85e-5	-0.00898	1	-2.19101
2	-0.35085	2.273407	2	-254.643
3	2.406522	-3.7568	3	1.721461

Table 4.26. Weight and bias values between input and hidden layer for T_{exh} prediction of Model 3

i	W_{1i}	W_{2i}	*i*	b_i
1	-0.30908	4.653108	1	47.37521
2	0.000499	0.001279	2	-1.467
3	-0.08345	0.051488	3	-22.8368
4	-10.5117	-1.91291	4	14.21196
5	-7.33084	23.05002	5	9.581845
6	-0.92752	1.302635	6	-1.12934
7	-2.09412	1.925848	7	5.266629

Comparison of actual and ANN predictions for testing section can easily be seen from the following Figures 4.31, 4.32 and 4.33.

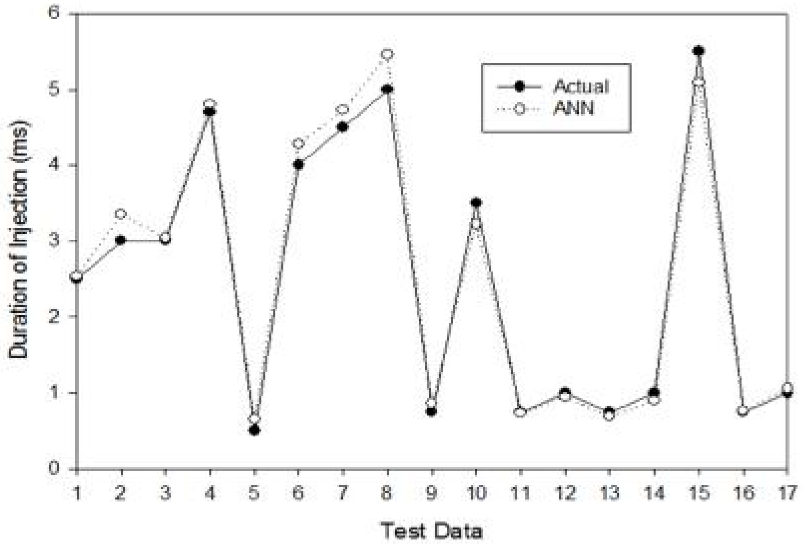


Figure 4.31. Testing section of DOI prediction with ANN for Model 3

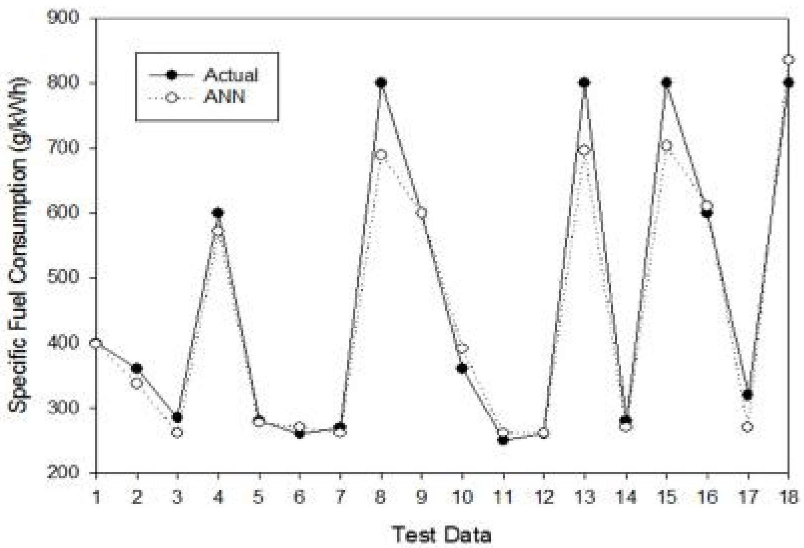


Figure 4.32. Testing section of SFC prediction with ANN for Model 3

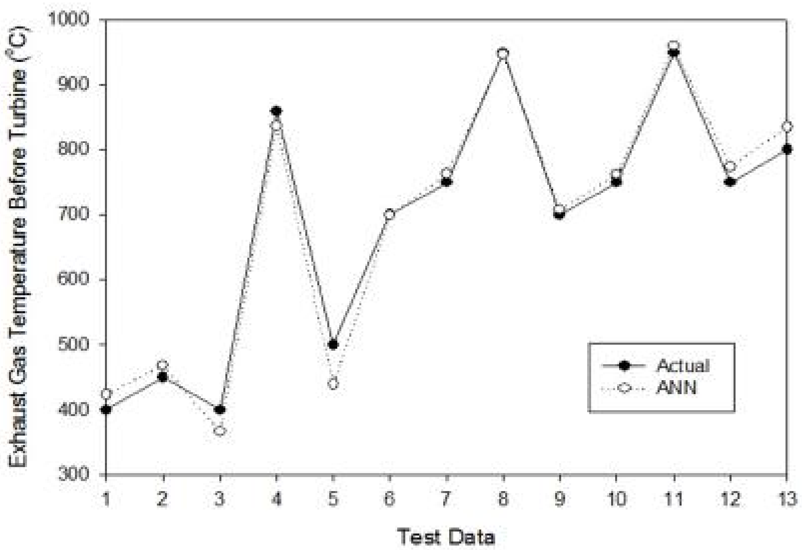


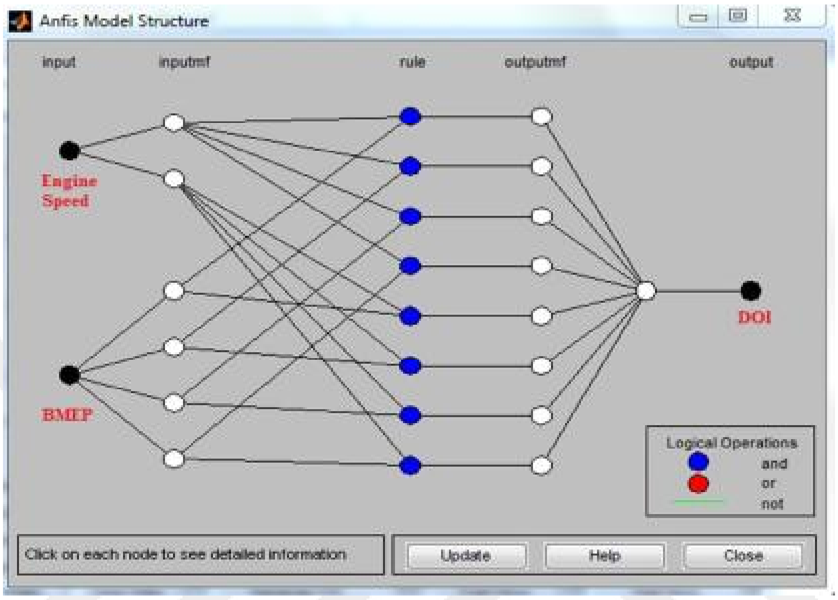
Figure 4.33. Testing section of T_{exh} prediction with ANN for Model 3

Table 4.27 shows the best ANFIS structures of Model 3 in order to obtain best estimation performance for each operational parameter. The best structures (number and type of membership functions) were set after some trial and errors and summarized in following table.

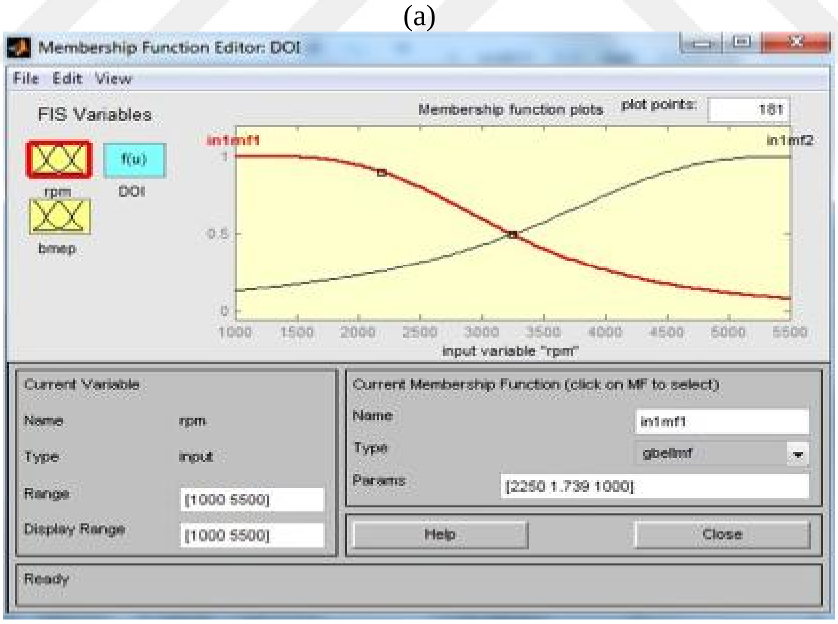
Table 4.27. Architectures of ANFIS models of Model 3

Estimated Parameter	Input			Output	FIS Generation	Optimization Method
	MF Number		MF Type	MF Type		
	Engine Speed	BMEP				
DOI	2	4	gbellmf	linear	grid partition	hybrid
SFC	2	7	trimf	linear	grid partition	hybrid
T_{exh}	4	4	trimf	linear	grid partition	hybrid

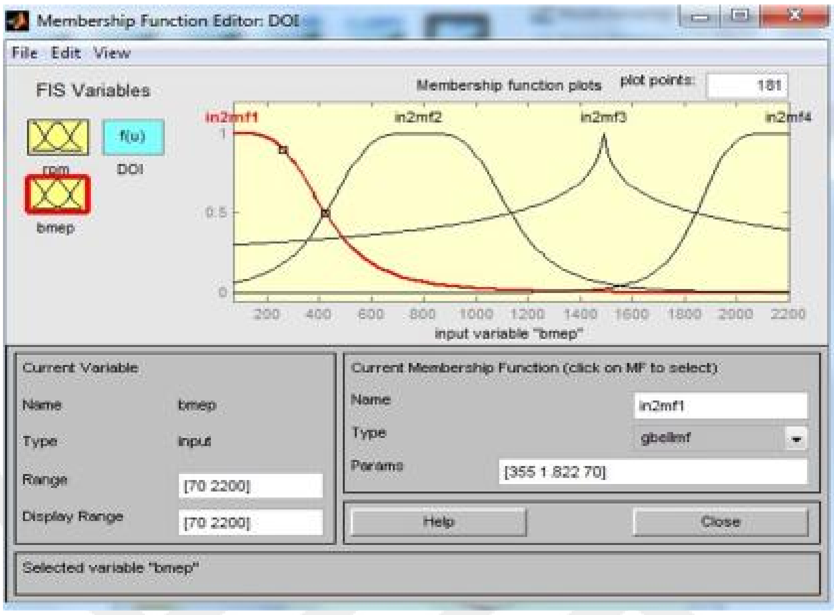
Details of generated ANFIS architecture for DOI, SFC and T_{exh} predictions of Model 3 can be seen in following Figures 4.34, 4.36 and 4.38. On the other hand, comparison of experimental and ANFIS predictions of engine-out parameters for testing section can easily be seen from the following Figure 4.35, 4.37 and 4.39.



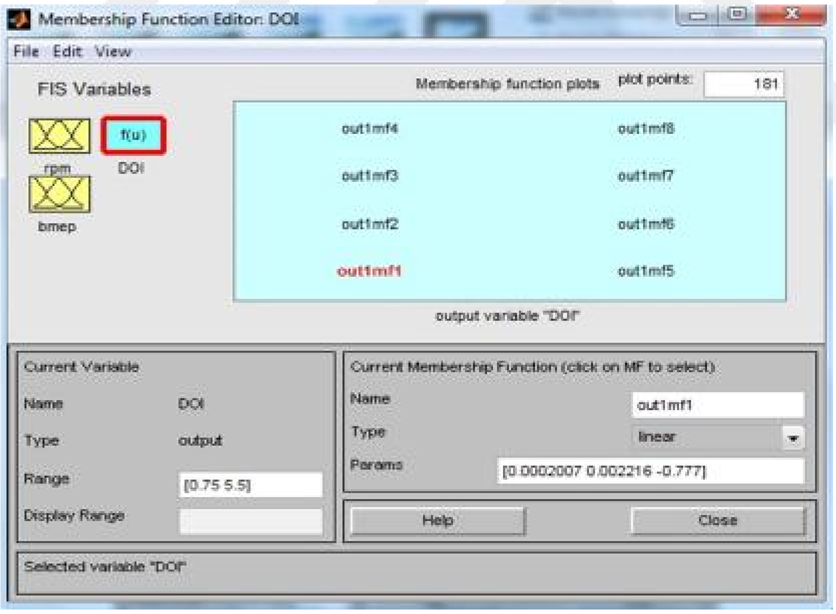
(a)



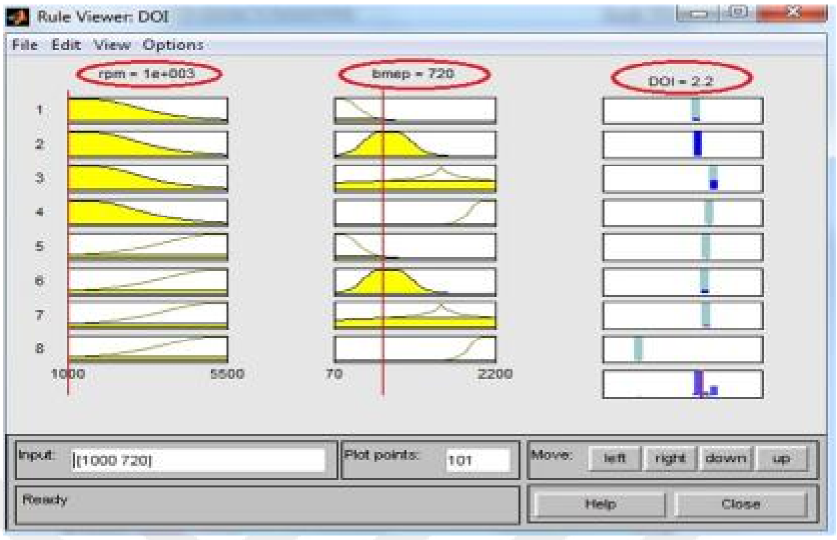
(b)


Membership Function Editor: DOI
File Edit View
FIS Variables
rpm
DOI
bmep
Membership function plots
plot points:
181
in2mf1
in2mf2
in2mf3
in2mf4
input variable "bmep"
Current Variable
Name bmep
Type input
Range [70 2200]
Display Range [70 2200]
Current Membership Function (click on MF to select)
Name in2mf1
Type gbellmf
Params [355 1.822 70]
Help
Close
Selected variable "bmep"

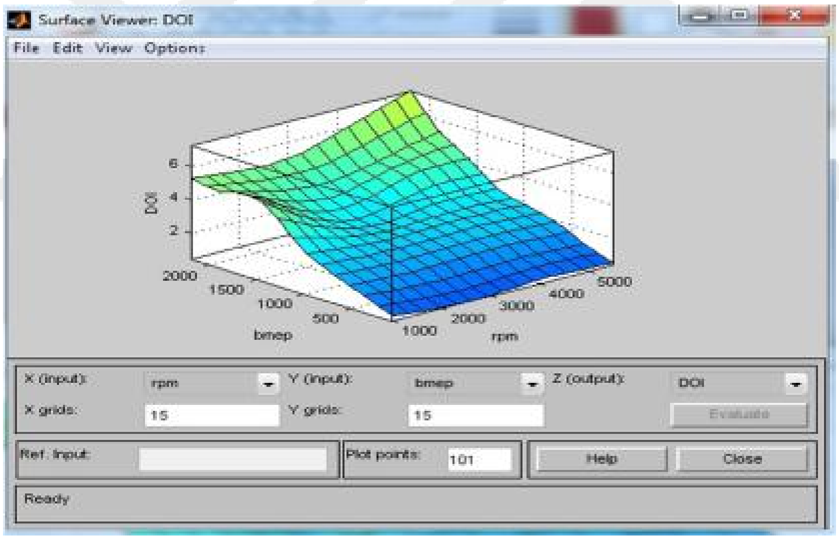
(c)


Membership Function Editor: DOI
File Edit View
FIS Variables
rpm
DOI
bmep
Membership function plots
plot points:
181
out1mf4
out1mf8
out1mf3
out1mf7
out1mf2
out1mf6
out1mf1
out1mf5
output variable "DOI"
Current Variable
Name DOI
Type output
Range [0.75 5.5]
Display Range
Current Membership Function (click on MF to select)
Name out1mf1
Type linear
Params [0.0002007 0.002216 -0.777]
Help
Close
Selected variable "DOI"

(d)



(e)



(f)

Figure 4.34.(a) ANFIS architecture (b) (c) membership functions of inputs (d) membership functions of output (e) fuzzy rules (f) surface view of rules of DOI prediction for Model 3

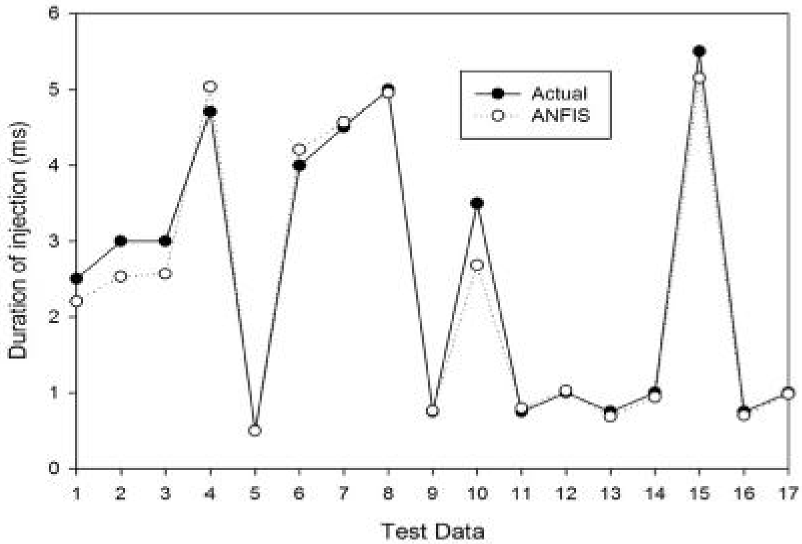
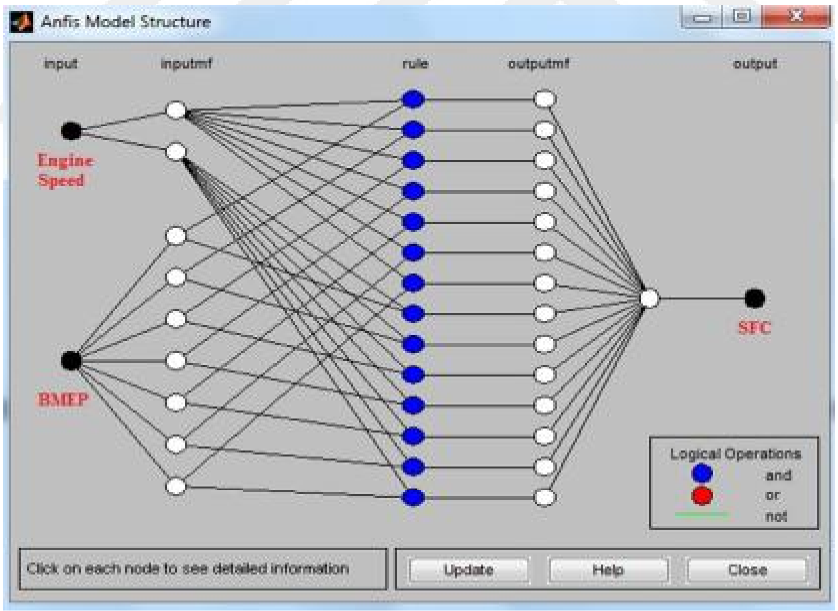
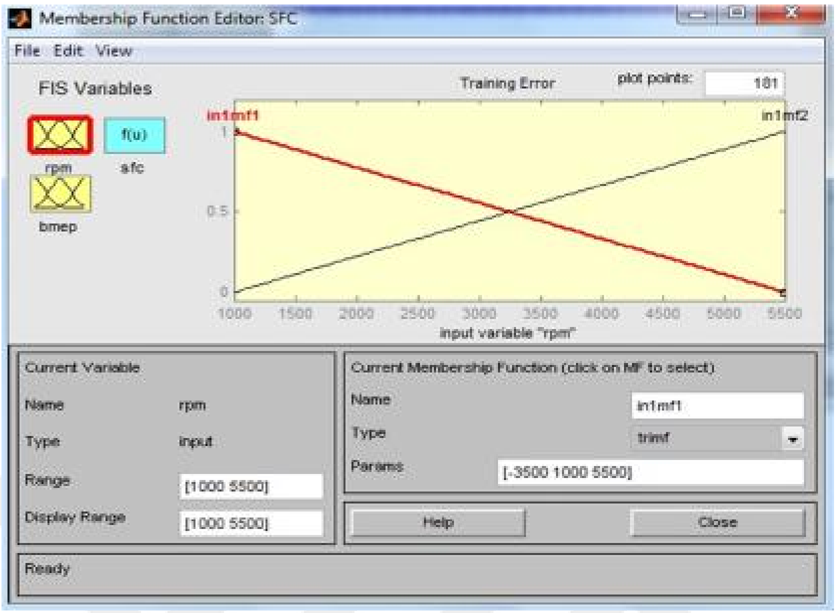


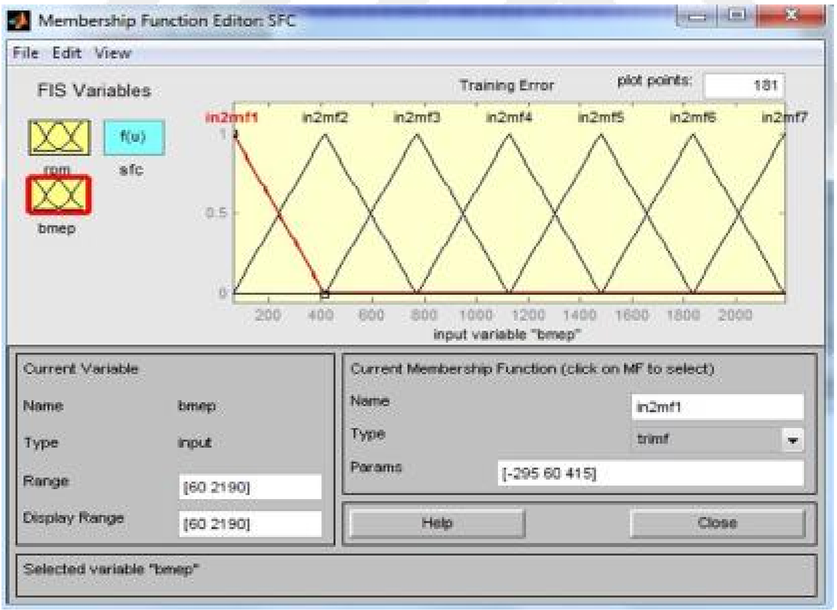
Figure 4.35.Testing section of DOI prediction with ANFIS for Model 3



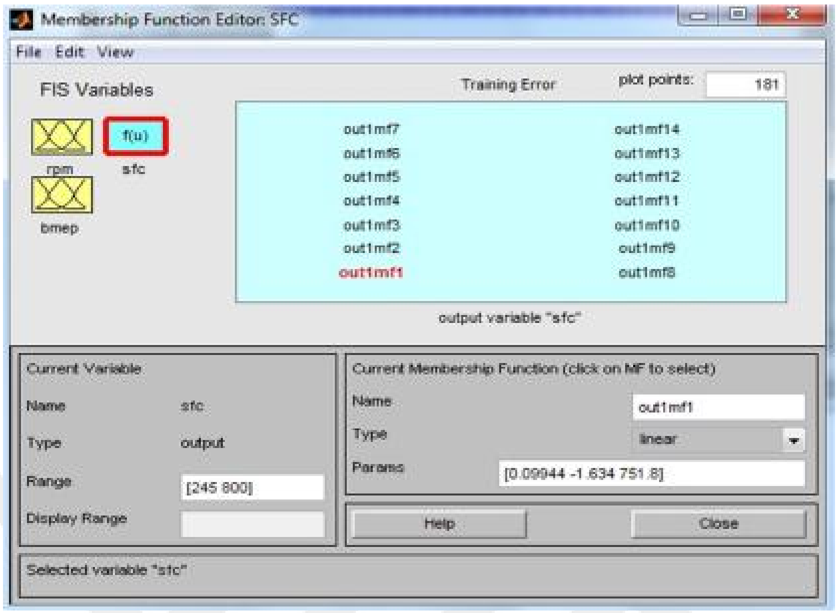
(a)


Membership Function Editor: SFC
File Edit View
FIS Variables
rpm
f(u)
sfc
bmep
Training Error
plot points:
181
in1mf1
in1mf2
1
0.5
0
1000 1500 2000 2500 3000 3500 4000 4500 5000 5500
input variable "rpm"
Current Variable
Name rpm
Type input
Range [1000 5500]
Display Range [1000 5500]
Current Membership Function (click on MF to select)
Name in1mf1
Type trimf
Params [-3500 1000 5500]
Help
Close
Ready

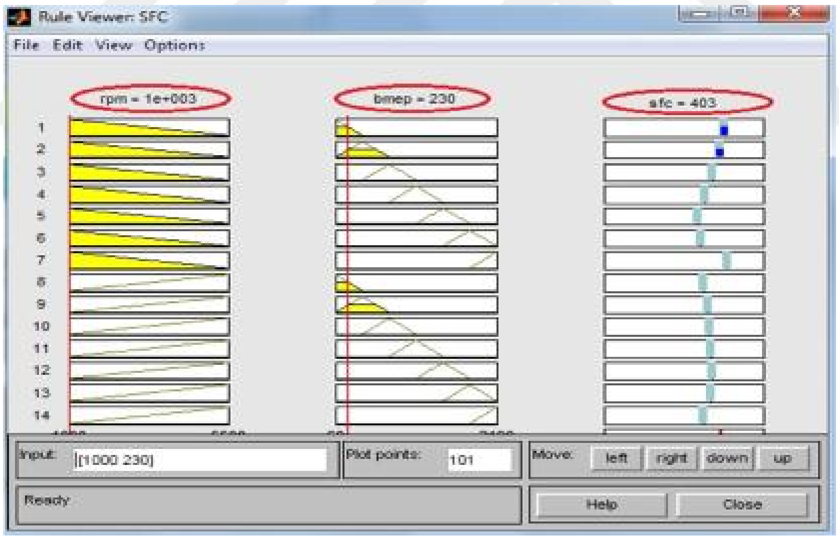
(b)


Membership Function Editor: SFC
File Edit View
FIS Variables
rpm
f(u)
sfc
bmep
Training Error
plot points:
181
in2mf1 in2mf2 in2mf3 in2mf4 in2mf5 in2mf6 in2mf7
1
0.5
0
200 400 600 800 1000 1200 1400 1600 1800 2000
input variable "bmep"
Current Variable
Name bmep
Type input
Range [60 2190]
Display Range [60 2190]
Current Membership Function (click on MF to select)
Name in2mf1
Type trimf
Params [-295 60 415]
Help
Close
Selected variable "bmep"

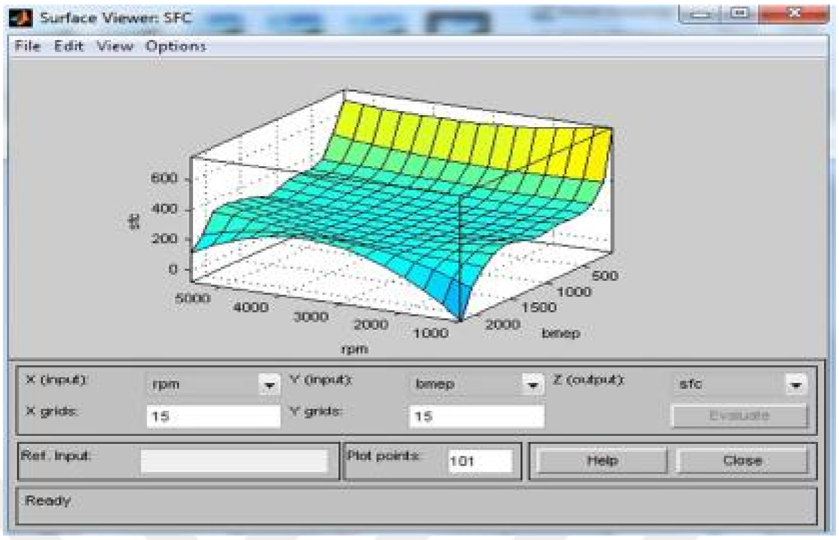
(c)


Membership Function Editor: SFC
File Edit View
FIS Variables
rpm
f(u)
sfc
bmep
Training Error
plot points:
181
out1mf7
out1mf6
out1mf5
out1mf4
out1mf3
out1mf2
out1mf1
out1mf14
out1mf13
out1mf12
out1mf11
out1mf10
out1mf9
out1mf8
output variable "sfc"
Current Variable
Name
sfc
Type
output
Range
[245 800]
Display Range
Current Membership Function (click on MF to select)
Name
out1mf1
Type
linear
Params
[0.09944 -1.634 751.8]
Help
Close
Selected variable "sfc"

(d)


Rule Viewer: SFC
File Edit View Options
rpm = 1e+003
bmep = 230
sfc = 403
1
2
3
4
5
6
7
8
9
10
11
12
13
14
Input:
[1000 230]
Plot points:
101
Move:
left
right
down
up
Ready
Help
Close

(e)



(f)

Figure 4.36.(a) ANFIS architecture (b) (c) membership functions of inputs (d) membership functions of output (e) fuzzy rules (f) surface view of rules of SFC prediction for Model 3

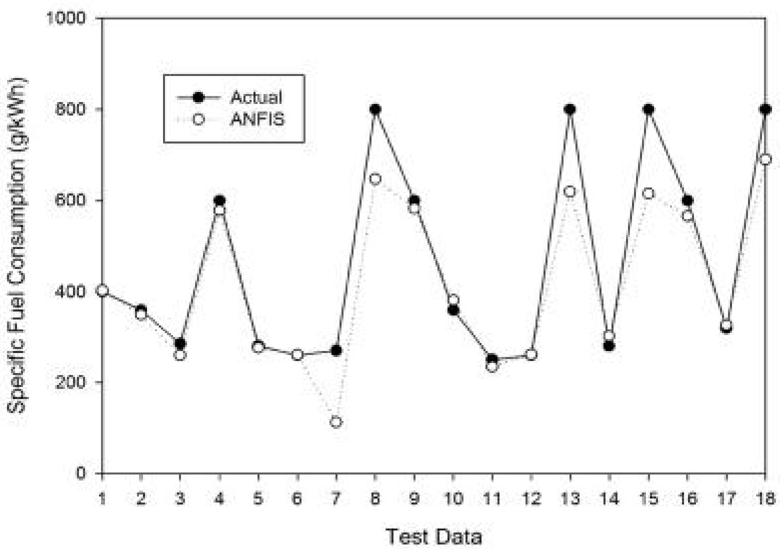
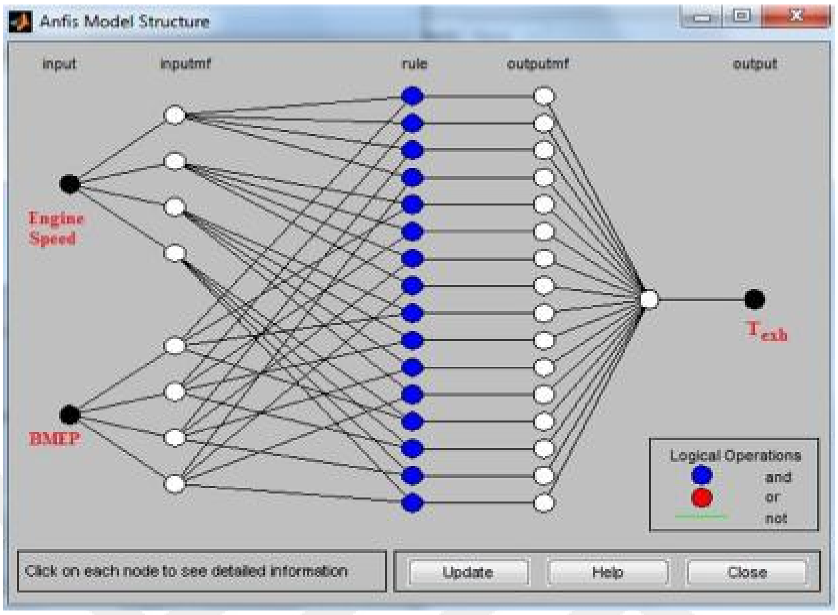
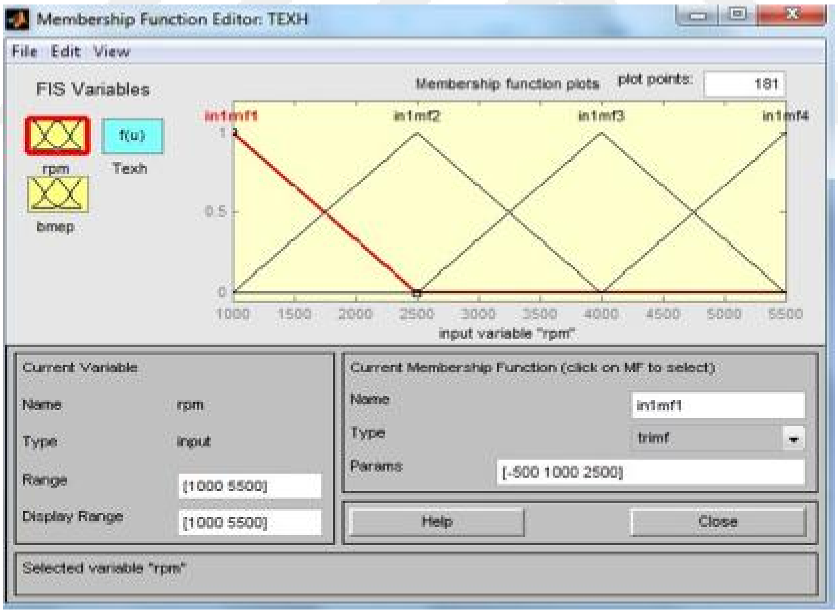


Figure 4.37.Testing section of SFC prediction with ANFIS for Model 3


Anfis Model Structure
input
inputmf
rule
outputmf
output
Engine Speed
BMEP
Texh
Logical Operations
and
or
not
Click on each node to see detailed information
Update
Help
Close

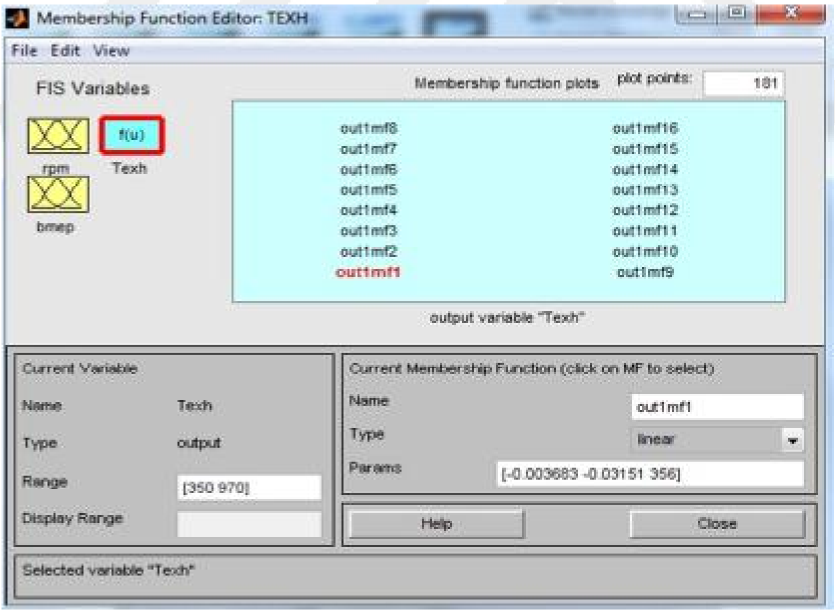
(a)


Membership Function Editor: TEXH
File Edit View
FIS Variables
rpm
f(u)
Texh
bmep
Membership function plots
plot points:
181
in1mf1
in1mf2
in1mf3
in1mf4
1
0.5
0
1000
1500
2000
2500
3000
3500
4000
4500
5000
5500
input variable "rpm"
Current Variable
Name
rpm
Type
input
Range
[1000 5500]
Display Range
[1000 5500]
Current Membership Function (click on MF to select)
Name
in1mf1
Type
trimf
Params
[-500 1000 2500]
Help
Close
Selected variable "rpm"

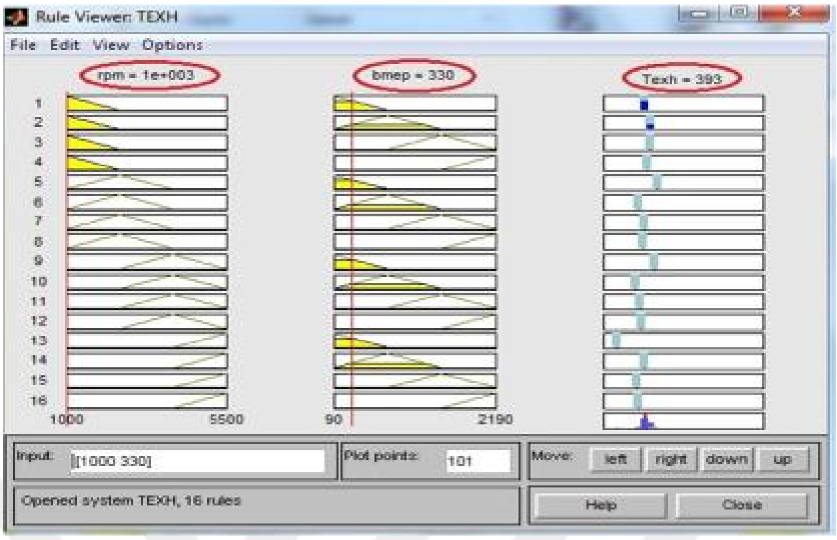
(b)


Membership Function Editor: TEXH
File Edit View
FIS Variables
rpm
f(u)
Texh
bmep
Membership function plots
plot points: 181
in2mf1
in2mf2
in2mf3
in2mf4
1
0.5
0
200 400 600 800 1000 1200 1400 1600 1800 2000
input variable "bmep"
Current Variable
Name bmep
Type input
Range [90 2190]
Display Range [90 2190]
Current Membership Function (click on MF to select)
Name in2mf1
Type trimf
Params [-610 90 790]
Help
Close
Selected variable "bmep"

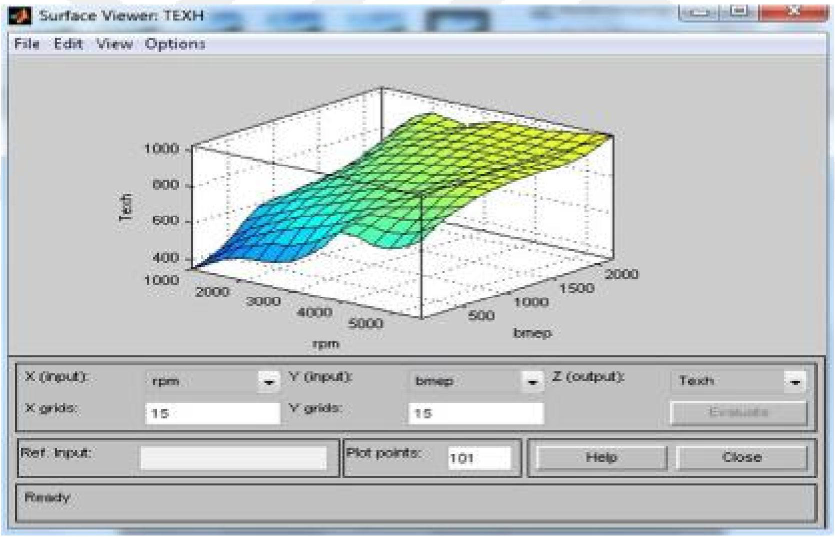
(c)


Membership Function Editor: TEXH
File Edit View
FIS Variables
rpm
f(u)
Texh
bmep
Membership function plots
plot points: 181
out1mf8 out1mf16
out1mf7 out1mf15
out1mf6 out1mf14
out1mf5 out1mf13
out1mf4 out1mf12
out1mf3 out1mf11
out1mf2 out1mf10
out1mf1 out1mf9
output variable "Texh"
Current Variable
Name Texh
Type output
Range [350 970]
Display Range
Current Membership Function (click on MF to select)
Name out1mf1
Type linear
Params [-0.003683 -0.03151 356]
Help
Close
Selected variable "Texh"

(d)



(e)



(f)

Figure 4.38.(a) ANFIS architecture (b) (c) membership functions of inputs (d) membership functions of output (e) fuzzy rules (f) surface view of rules of T_{exh} prediction for Model 3

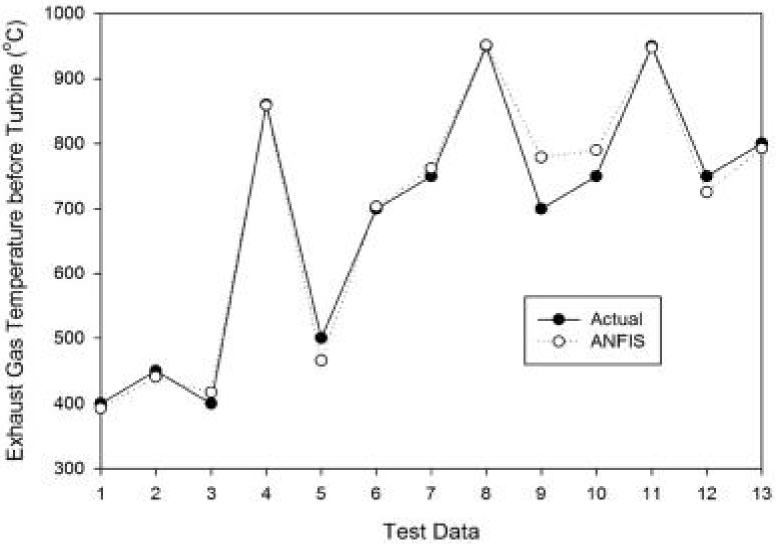


Figure 4.39.Testing section of T_{exh} prediction with ANFIS for Model 3

The summary of above figures of Model 3 can be found in Table 4.28. As in previous models ANN and ANFIS approximations gave more satisfactory results for estimation of engine operational parameters.

Table 4.28.Prediction performance evaluation for Model 3

Estimated Parameter	***Method***	***MAPE (%)***
		Testing
DOI	LR	13.83
	NLR	10.7
	ANN	7.82
	ANFIS	7.07
SFC	LR	26.24
	NLR	17.3
	ANN	5.87
	ANFIS	10.34
T_{exh}	LR	6.52
	NLR	10.66
	ANN	3.59
	ANFIS	2.96

4.4. Prediction of Engine Vibration Level of HHO Gas Generator Installed Compression Ignition Engine Operated with Different Diesel-Biodiesel Blends (Model 4)

In Model 4, engine vibration level was estimated by using ANN and ANFIS. The engine used for tests is naturally aspirated compression ignition engine. The engine is the same engine in Model 1 and 2. Specifications can be seen from Table 4.1 and 4.2. Vibration characteristics of engine were tested with different fuel mixtures and with various amounts of HHO addition (2 - 4 - 6 L/min) into the intake manifold. Fuels are pure diesel, 20% and 40% sunflower biodiesel – diesel blend, 20% and 40% canola biodiesel – pure diesel blend, 20% and 40% corn biodiesel – pure diesel blend and their specifications are D100, SB20 SB40, CaB20, CaB40, CoB20, CoB40, respectively. The engine was operated at 1200, 1500, 1800, 2100 and 2400 rpm engine speed and tests were achieved under no load condition to reduce dynamometer vibration level. The vibration data was taken from the engine by Soundbook™ universal portable measuring system operated by SAMURAI v2.6 software from SINUS Messtechnik GmbH and an accelerometer from PCB electronic (model no: 356A33) has 1.02 mV/(m/s^2) sensitivity and ±4905 m/s^2 measurement range (Uludamar et al., 2017).

Since regression analysis in the previous models did not give satisfactory results for estimation of engine-out parameters, only ANN and ANFIS modelling was applied to the data in Model 4.

Engine was operated with 6 different fuels in order to get vibration levels. Additionally, HHO gas was added with various flow rates through intake manifold. 70% of total data set (84) was used as training data and remaining randomly selected 30% of total data set (36) was used to test the models. General structure of ANN used in Model 4 was shown in Figure 4.40. As seen from figure that, engine speed (rpm), HHO flow rate (HHO), cetane number (CN), lower heating value (LHV) were selected as input to be able to estimate vibration level. 2 neurons for hidden layer gave satisfactory results after trying different numbers. The learning algorithm was Levenberg-Marquardt and transfer functions were logsig and purelin for hidden and output layer, respectively.

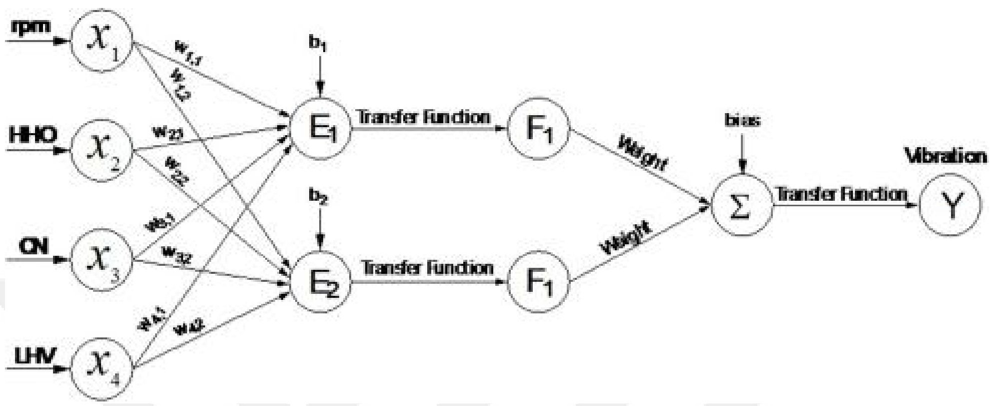


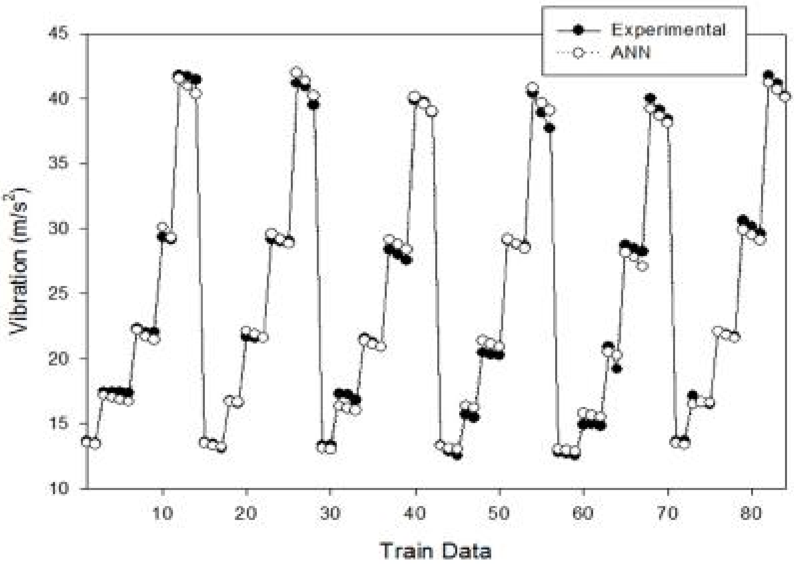
Figure 4.40. ANN architecture in Model 4 (Uludamar et al., 2017)

Vibration level of engine can easily be calculated with use of the following formulas in Table 4.29.

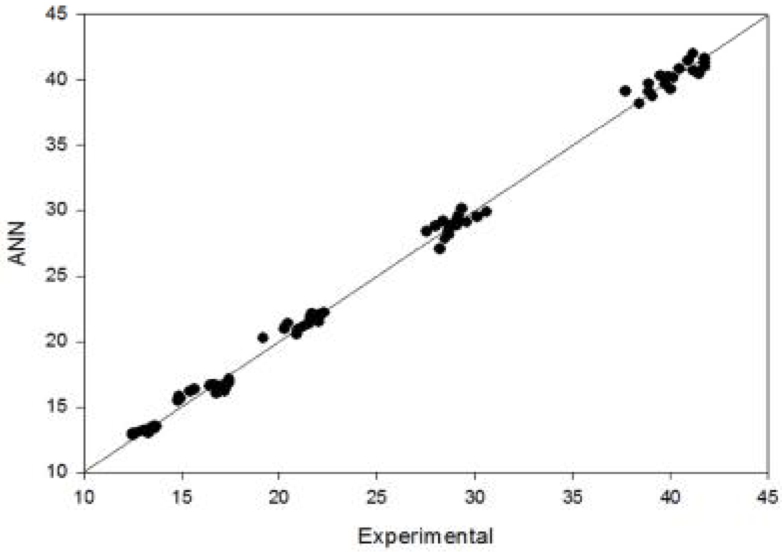
Table 4.29 Mathematical background behind ANN predictions for Model 4

$Vibration = -0.42537 * F_1 - 391.908 * F_2 + 400.5484$
$F_1 = \dfrac{1}{1 + e^{-(-0.94589*rpm-57.5043*HHO-61.2878*CN+5.723653*density+194.8979)}}$ $F_2 = \dfrac{1}{1 + e^{-(-0.0016*rpm+0.009868*HHO+0.031653*CN+0.013392*density-6.87912)}}$

Comparison of experimental and ANN predictions both for training and testing sections can easily be seen from the following Figure 4.41 and 4.42, respectively.



(a)



(b)

Figure 4.41. (a) Training section (b) correlation of vibration prediction with ANN for Model 4

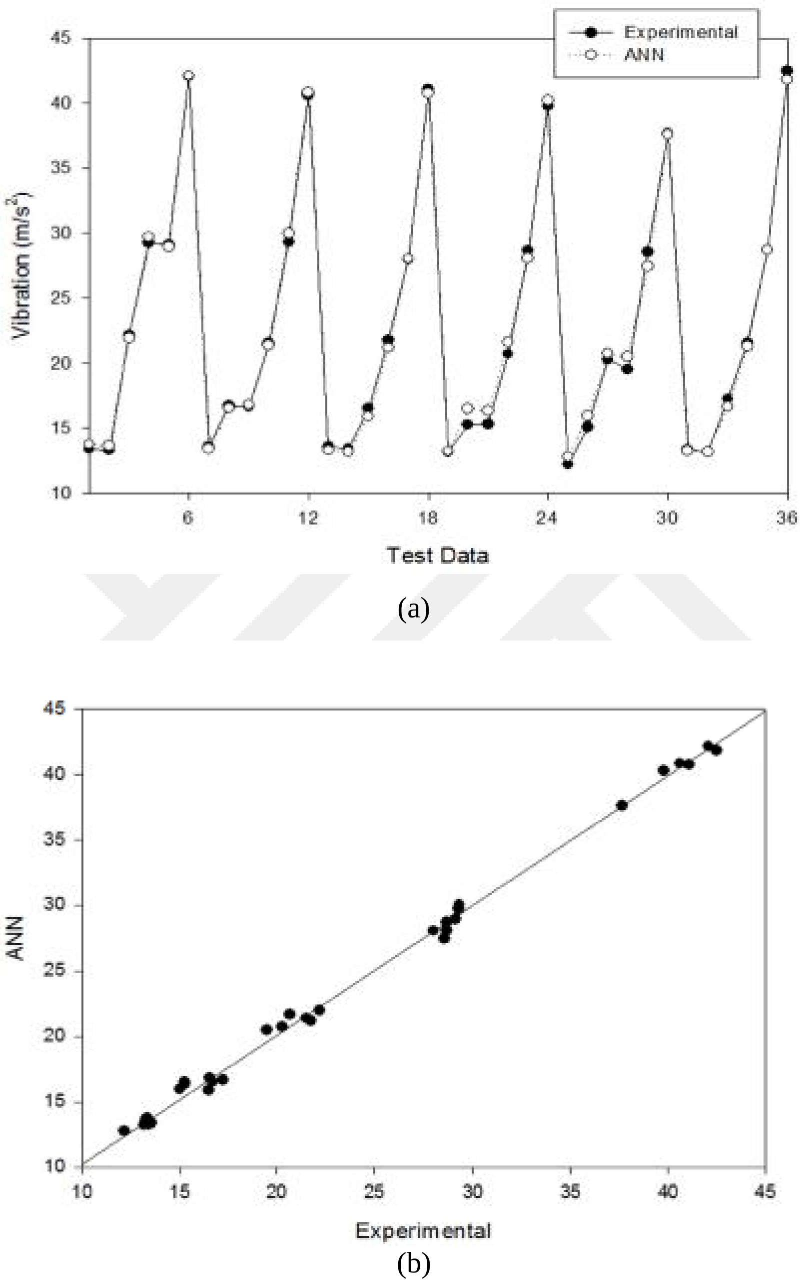
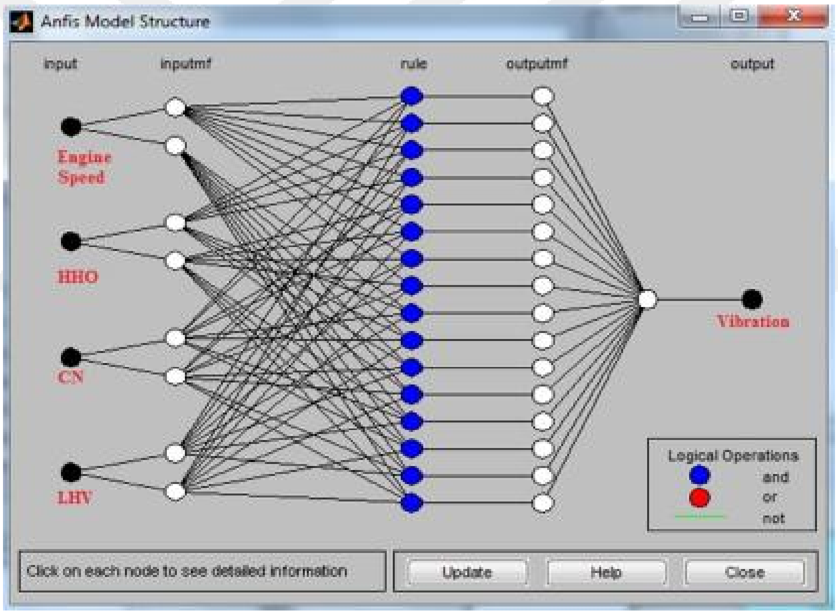


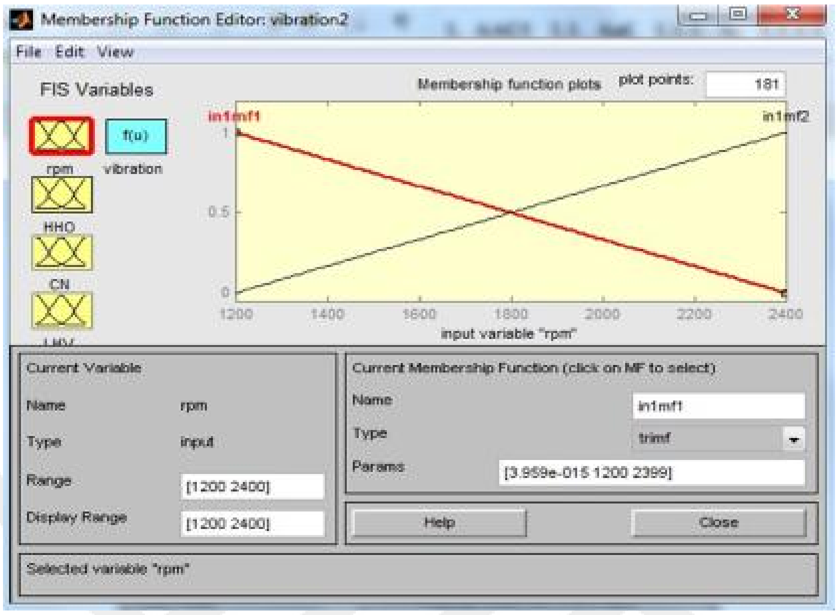
Figure 4.42. (a) Testing section (b) correlation of vibration prediction with ANN for Model 4

In ANFIS model, data was separated as training and testing section similar within ANN. Sugeno type ANFIS architecture was used. Trimf type membership function was selected for each input parameters and the number of membership functions for each input is 2. Linear was selected as output membership function. FIS generated by grid partition and optimization method is hybrid.

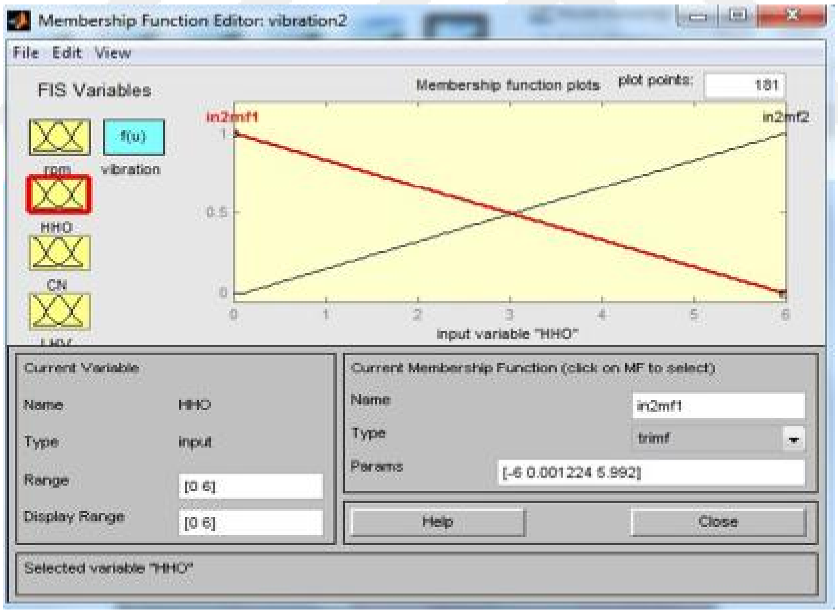
Details of generated ANFIS architecture for engine vibration predictions of Model 4 can be seen in following Figure 4.43. On the other hand, comparison of experimental and ANFIS predictions both for training and testing sections can easily be seen from the following Figure 4.44 and 4.45, respectively.



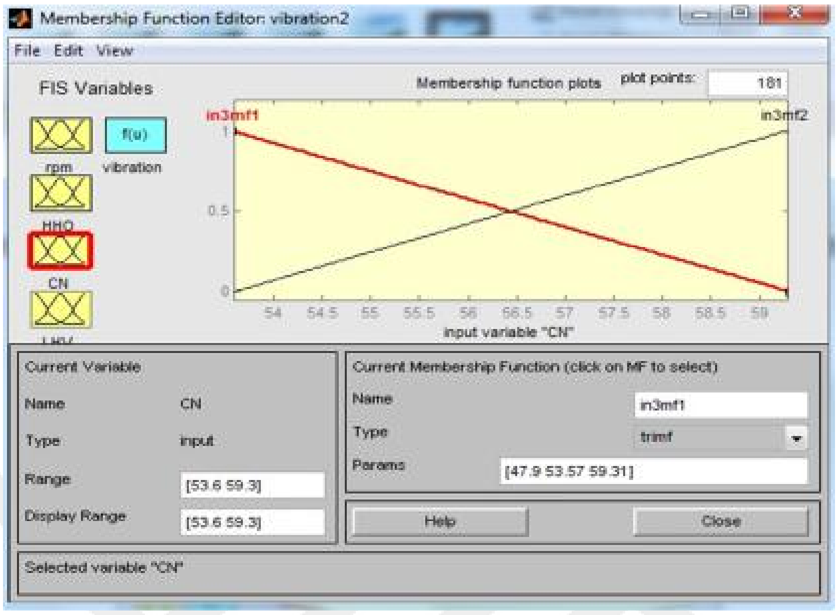
(a)


Membership Function Editor: vibration2
File Edit View
FIS Variables
rpm
f(u)
vibration
HHO
CN
Membership function plots
plot points:
181
in1mf1
in1mf2
input variable "rpm"
Current Variable
Name
rpm
Type
input
Range
[1200 2400]
Display Range
[1200 2400]
Current Membership Function (click on MF to select)
Name
in1mf1
Type
trimf
Params
[3.959e-015 1200 2399]
Help
Close
Selected variable "rpm"

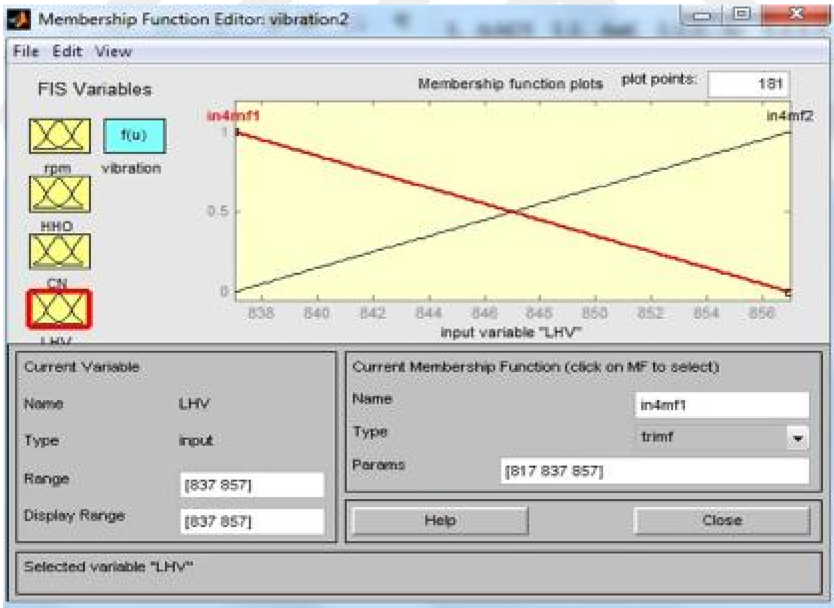
(b)


Membership Function Editor: vibration2
File Edit View
FIS Variables
rpm
f(u)
vibration
HHO
CN
Membership function plots
plot points:
181
in2mf1
in2mf2
input variable "HHO"
Current Variable
Name
HHO
Type
input
Range
[0 6]
Display Range
[0 6]
Current Membership Function (click on MF to select)
Name
in2mf1
Type
trimf
Params
[-6 0.001224 5.992]
Help
Close
Selected variable "HHO"

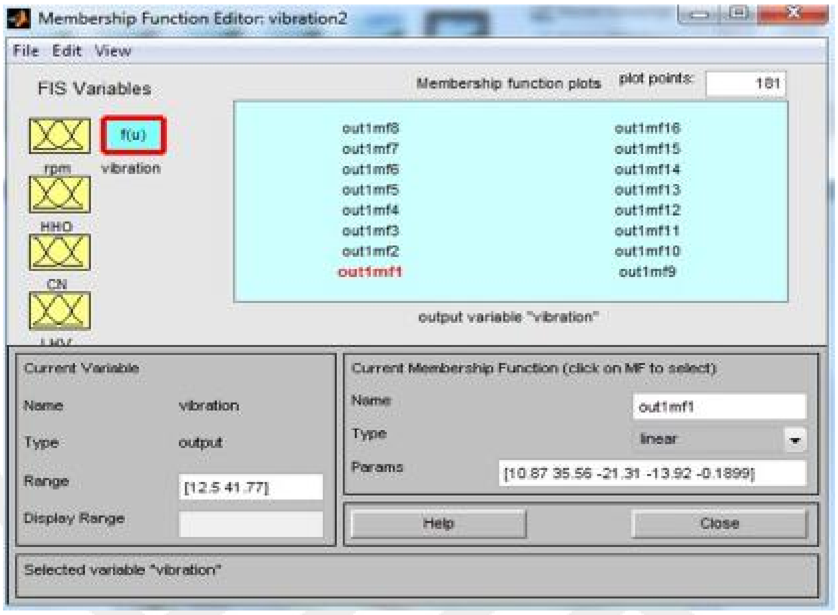
(c)


Membership Function Editor: vibration2
File Edit View
FIS Variables
rpm
f(u)
vibration
HHO
CN
LHV
Membership function plots
plot points: 181
in3mf1
in3mf2
input variable "CN"
Current Variable
Name CN
Type input
Range [53.6 59.3]
Display Range [53.6 59.3]
Current Membership Function (click on MF to select)
Name in3mf1
Type trimf
Params [47.9 53.57 59.31]
Help
Close
Selected variable "CN"

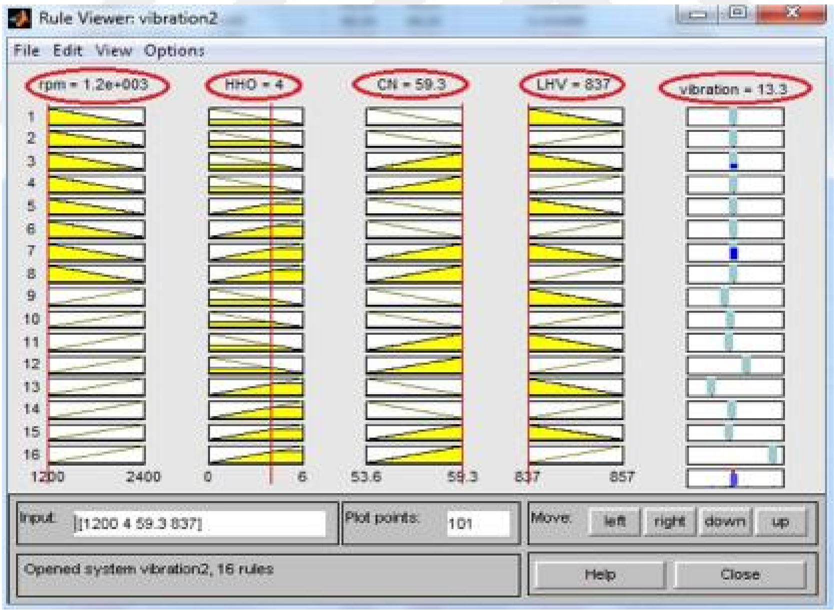
(d)


Membership Function Editor: vibration2
File Edit View
FIS Variables
rpm
f(u)
vibration
HHO
CN
LHV
Membership function plots
plot points: 181
in4mf1
in4mf2
input variable "LHV"
Current Variable
Name LHV
Type input
Range [837 857]
Display Range [837 857]
Current Membership Function (click on MF to select)
Name in4mf1
Type trimf
Params [817 837 857]
Help
Close
Selected variable "LHV"

(e)

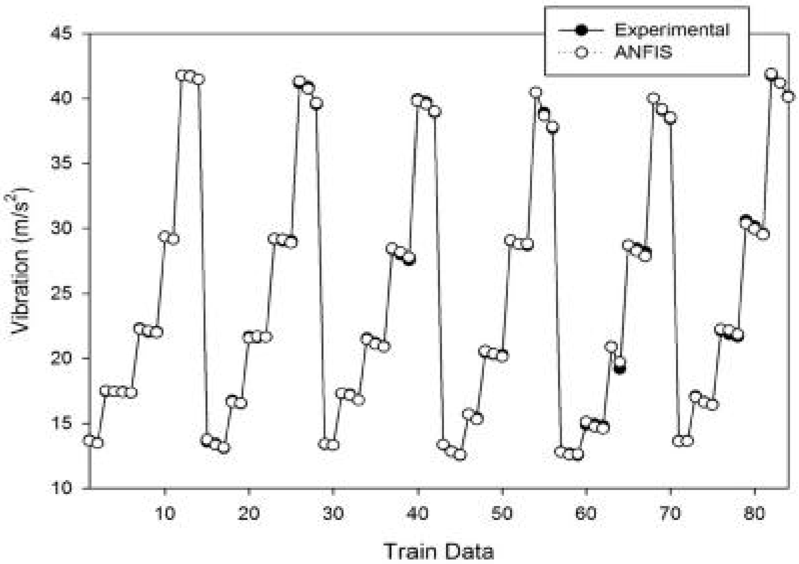


(f)

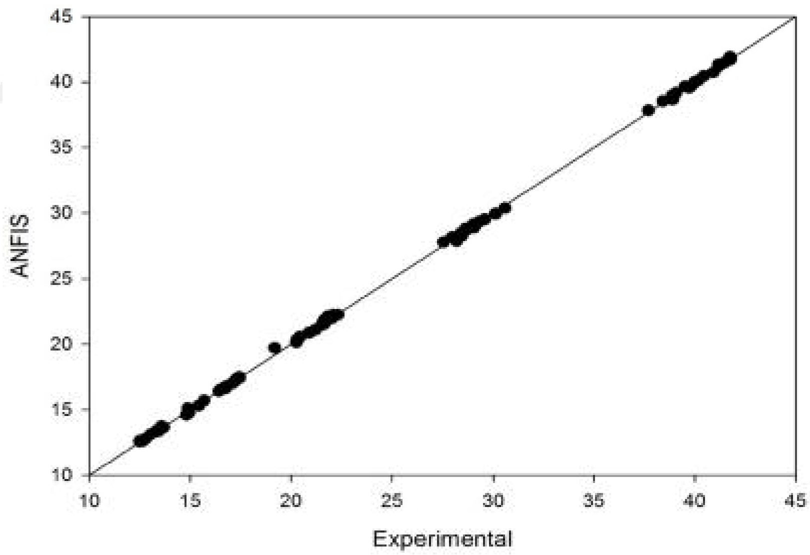


(g)

Figure 4.43. (a) ANFIS architecture (b) (c) (d) (e) membership functions of inputs (f) membership functions of output (g) fuzzy rules of vibration prediction for Model 4

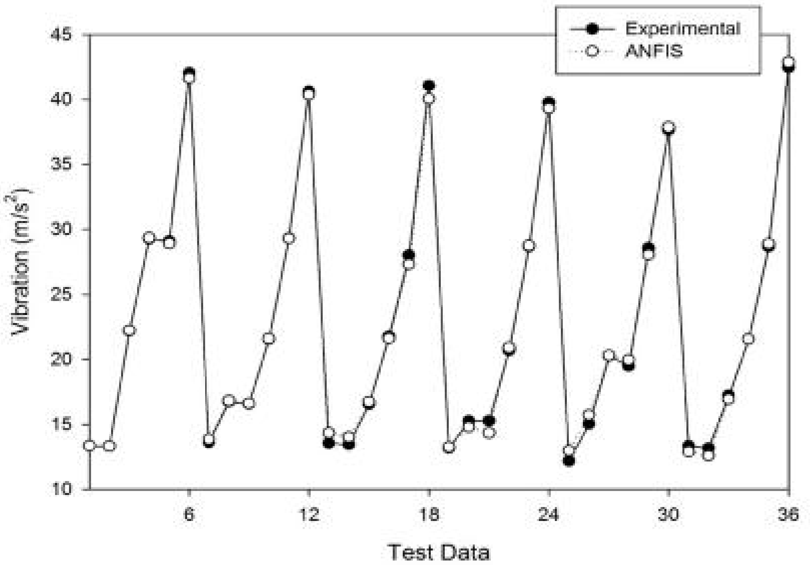


(a)

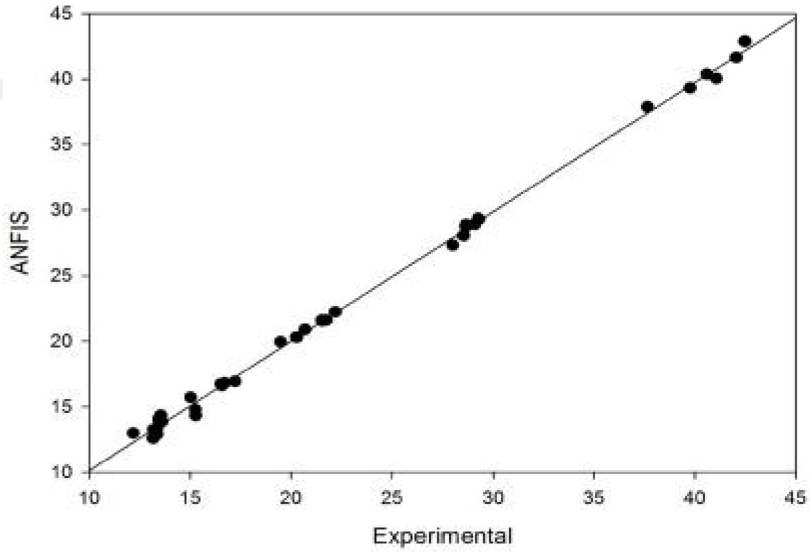


(b)

Figure 4.44. (a) Training section (b) correlation of vibration prediction with ANFIS for Model 4



(a)



(b)

Figure 4.45. (a) Testing section (b) correlation of vibration prediction with ANFIS for Model 4

Acceptable predictions were conducted by use of both ANN and ANFIS methods according to above figures. The MAPE values of training and testing sections for ANN were 2 and 2.02. The MAPE values of training and testing sections for ANFIS were 0.44 and 1.73.

5. CONCLUSIONS

Combustion phenomenon contains highly non-linear and complex relations. Therefore, black-box modelling such as ANN and ANFIS can be used in internal combustion engine applications. Mathematical models can be created instead of experimental tests in order to save cost and time.

- The main aim of this work is comprehensive analysis of usability of AI techniques for various engine-out parameters estimations.
- Artificial neural network and adaptive neuro fuzzy inference system were used as artificial intelligence technique.
- Four different engine models were handled which intended to estimate various engine-out parameters. In Model 1, performance and emission parameters of a diesel engine operated with biodiesel-alcohol mixtures were estimated. In Model 2, performance and emission parameters of a diesel engine operated with diesel fuel with nanoparticle additives were estimated. In model 3, various operational parameters of a spark ignition engine operated with 95 RON gasoline fuel were estimated. In model 4, vibration characteristic of a diesel engine operated with different diesel-biodiesel blends with HHO gas addition into intake manifold were estimated.
- For Model 1, the MAPE values for testing period of LR and ANN models were obtained between 11.9-24.96% and 3.56-16.22%, respectively. For Model 2, the MAPE values for testing period of LR, NLR, ANN and ANFIS models were obtained between 6-17.6%, 5.59-10.63%, 1.22-5.39% and 1.09-4.89%. For model 3, the MAPE values for testing period of LR, NLR, ANN and ANFIS models were obtained between 6.52-26.24%, 10.66-17.3%, 3.59-7.82% and 2.96-10.34%. For model 4, the MAPE

values for testing period of ANN and ANFIS models were obtained 2.02% and 1.73%, respectively.

- ANFIS and ANN prediction results were better than classical regression analysis.
- Least difference between experimental and prediction results were obtained with use of ANFIS.
- The number of data used in training period highly affects the performance of network. It means that providing more experimental data in training period will improve the generalization capacity of models.
- The AI techniques are highly recommended for the estimation of engine-out parameters instead of time consuming, complex and costly experimental studies of internal combustion engines.

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CURRICULUM VITAE

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APPENDIX

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ORIGINAL ARTICLE

Comparison of linear regression and artificial neural network model of a diesel engine fueled with biodiesel-alcohol mixtures

CrossMark

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KEYWORDS

Diesel engine;
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Linear regression;
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Abstract This study deals with usage of linear regression (LR) and artificial neural network (ANN) modeling to predict engine performance; torque and exhaust emissions; and carbon monoxide, oxides of nitrogen (CO, NOx) of a naturally aspirated diesel engine fueled with standard diesel, peanut biodiesel (PME) and biodiesel-alcohol (EME, MME, PME) mixtures. Experimental work was conducted to obtain data to train and test the models. Backpropagation algorithm was used as a learning algorithm of ANN in the multilayered feedforward networks. Engine speed (rpm) and fuel properties, cetane number (CN), lower heating value (LHV) and density (ρ) were used as input parameters in order to predict performance and emission parameters. It was shown that while linear regression modeling approach was deficient to predict desired parameters, more accurate results were obtained with the usage of ANN.

1. Introduction

In today's world, high thermal efficiency of diesel engine makes them attractive and popular to use. Conventionally, compression ignition engines operate with diesel fuel derived from crude oil [1]. In the late 1970s and early 1980s, an energy crisis occurred over world due to the depletion of fossil based fuels [2]. Therefore, scientists have been working on this issue for many years. Recently, usage of alternative fuels in internal combustion engines has been an important research area. In this respect, vegetable oils, and alcohols such as ethanol and methanol have been investigated to be able to use in internal combustion engines [3]. Requirement of little or no engine modification makes those alternatives remarkable. There are lots of study about fuel properties, performance and emission characteristics of an internal combustion engine operated with various alternative fuels [4–10].

Determination of performance and emission characteristics of an internal combustion engine is complex, time consuming and costly [11]. Therefore, in order to eliminate these disadvantages and complexities, performance and emission of an engine can be modeled with using artificial neural network (ANN). An ANN system works as a biological neuron. Neurons receive input from the source, perform a non-linear operation, and predict final output [12]. In recent years, parallel to

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Original Paper

Comparative analysis of various modelling techniques for emission prediction of diesel engine fueled by diesel fuel with nanoparticle additives[§]

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Abstract

In this study, emissions of compression ignition engine fueled by diesel fuel with nanoparticle additives was modeled by regression analysis, artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) methods. Cetane number (CN) and engine speed (rpm) were selected as input parameters for estimation of carbon monoxide (CO), oxides of nitrogen (NOx), and carbon dioxide (CO_2) emissions. The results of estimation techniques were compared with each other and they showed that regression analysis was not accurate enough for prediction. On the other hand, ANN and ANFIS modelling techniques gave more accurate results with respect to regression analysis; linear and non-linear. Especially ANFIS models can be suggested as estimation method with minimum error compared to experimental results.

Keywords: Adaptive neuro fuzzy inference system; Artificial neural network; Diesel engine; Regression analysis

1. INTRODUCTION

In recent years, depletion of fossil fuels forces researchers to search new alternative fuels. In literature, there are a lot of studies about fuels which have potential to replace fossil fuels used in internal combustion engines. In this respect, various biofuels and alcohols seem as good option [1]. In addition to scarcity of conventional fuels, efforts on performance en-hancement and emission reduction of engines are the other important issues on which engineers and engine manufacturers are working on it. Especially, the stringent emission legislations enforced manufacturers to develop new technologies [2]. Traditional engine research and development studies are both difficult and costly to meet emission limits imposed by legislations. Therefore, these costly studies are replaced by various cost-effective approaches as artificial neural networks (ANN) and computational fluid dynamics (CFD) [3]. ANNs are nonlinear computer algorithms, which can model the behavior of complex nonlinear processes. Recently, this method has been widely applied to various disciplines as automotive engineering [4]. Yusaf et al. studied the effect of using CPO (crude palm oil) - OD (ordinary diesel) blends as fuel on the performance of CI (compression ignition) engine. In addition, engine power output, fuel consumption, and exhaust-gas emission are evaluated and then predicted using ANN technique [5]. Shanmugam et al. used ANN modeling to predict the performance and exhaust emissions of the diesel engine using hybrid fuel and they revealed that the ANN approach could be confidently used to predict the performance and emissions of the diesel engine accurately [6]. Ghazikhani and Mirzaii predicted soot emission of a waste-gated turbo-charged DI diesel engine using ANN. The results showed the ANN approach can be used to accurately predict soot emis-sion of a turbo-charged diesel engine in different opening ranges of waste-gate (ORWG) [7].

On the other hand, there is another modelling approach called as adaptive neuro fuzzy inference system (ANFIS) which combines the benefits of ANNs and fuzzy logic. ANFIS modelling is very powerful technique with the ability of interpretable if-then rules [8]. Isin and Uzunsoy presented fuzzy logic-based prediction method to reveal the performance and emission characteristics of a single cylinder spark ignition (SI) engine, which uses different fuel mixtures [9]. Ozkan et al. used ANFIS to estimate the effect of methanol mixtures in different proportions on emission and performance of the motor [10]. Al-Hinti et al. used a neuro-fuzzy interface system to study the effect of boost pressure on the efficiency, brake mean effective pressure (BMEP), and the brake specific fuel consumption (BSFC) of a single cylinder diesel engine.

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ESTIMATION OF OPERATIONAL PARAMETERS FOR A DIRECT INJECTION TURBOCHARGED SPARK IGNITION ENGINE BY USING REGRESSION ANALYSIS AND ARTIFICIAL NEURAL NETWORK

by

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This study was aimed at estimating the variation of several engine control parameters within the rotational speed-load map, using regression analysis and artificial neural network techniques. Duration of injection, specific fuel consumption, exhaust gas at turbine inlet, and within the catalytic converter brick were chosen as the output parameters for the models, while engine speed and brake mean effective pressure were selected as independent variables for prediction. Measurements were performed on a turbocharged direct injection spark ignition engine fueled with gasoline. A three-layer feed-forward structure and back-propagation algorithm was used for training the artificial neural network. It was concluded that this technique is capable of predicting engine parameters with better accuracy than linear and non-linear regression techniques.

Key words: *turbocharged direct injection spark ignition engine, regression analysis, artificial neural network, estimation*

Introduction

Given their high power to weight ratio and good efficiency, internal combustion engines (ICE) are used on a wide scale for transportation and power production. The ICE are generally driven by conventional petroleum based fossil fuels. However, fossil fuel depletion has been identified as a future challenge by scientists [1]. Both alternative fuel investigations and studies aimed at efficiency enhancement require intensive laboratory work. Experimental studies are time consuming and costly processes. In parallel to the development of computer technology, use of various modeling techniques is being widespread. Artificial neural network (ANN) is one of the leading techniques among these. It is a computational modeling technique that consists of interconnected adaptive simple processing elements referred as neurons and nodes [2]. In recent years, several researchers have applied neural networks to ICE for prediction of performance, emissions, and combustion characteristics. Kapusuz *et al.* [3] investigated various alcohol-unleaded gasoline mixtures that can be used without modifications in a spark-ignition (SI) engine. Their paper demonstrated that ANN can successfully be used as an alter-

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Evaluation of vibration characteristics of a hydroxyl (HHO) gas generator installed diesel engine fuelled with different diesel–biodiesel blends

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ABSTRACT

There are two main reasons of alternative fuel search of scientists: environmental problems resulted from combustion of fossil fuels and limited reserves of crude oil. Biodiesel and Hydrogen (H_2) are two of the most promising alternative fuels with their environmental friendly combustion profiles. The aim of this study was to evaluate vibration level of a hydroxyl (HHO) gas generator installed and diesel engine using different kinds of biodiesel fuels. In this study, at different flow rates, the effect of HHO gas addition on engine vibration performance was investigated with a Mitsubishi Canter 4D34-2A diesel engine. HHO gas introduced to the test engine via its intake manifold with 2, 4 and 6 L per minute (LPM) flow rates when the engine was fuelled with sunflower, canola, and corn biodiesels. The vibration data was collected between 1200 and 2400 rpm engine speeds by 300 rpm intervals. Finally, artificial neural network (ANN) approach was conducted in order to predict the effect of fuel properties and HHO amount on engine vibration level.

Introduction

The requirement of an alternative choice for fossil fuels becomes the main focus of today's scientific researches since the world is facing challenges of energy deficiency and increase of exhaust gas concentration from industrial plants and automobiles into the atmosphere is the most threatening factor of global warming [1–4]. With its high energy-density; wider flammability limits and high burning velocity properties, hydrogen (H_2) can be best candidate of fossil fuels. Another advantage of hydrogen gas is; it only forms water as a result of its simple reaction with oxygen due to its chemical structure of non-content of carbon atoms [5].

Hydroxyl (HHO) is a gaseous fuel which contains a mixture of hydrogen (H_2) and oxygen (O_2) gases and can be obtained directly by electrolysis of water. HHO is an odourless, colourless gas which is lighter than air. The flammability of HHO gas is much more compared to diesel [6]. However, low density of HHO is a very important drawback creating some problems in carriage and storage. In addition, mixture of

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