ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

MODELLING THE EFFECTS OF BRAND IMAGE COMPONENTS ON ADVERTISING AWARENESS USING A NEURO-FUZZY SYSTEM

M.Sc. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

MARKA İMAJ BİLEŞENLERİNİN REKLAM HATIRLANIRLIĞI ÜZERİNE ETKİSİNİN BULANIK SİNİR AĞLARI SİSTEMİ İLE MODELLENMESİ

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Ali FAHMI, a M.Sc. student of ITU Graduate School of Science Engineering and Technology 507131002 successfully defended the thesis entitled “MODELLING THE EFFECTS OF BRAND IMAGE COMPONENTS ON ADVERTISING AWARENESS USING A NEURO-FUZZY SYSTEM”, which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my kind parents and lovely sister,

FOREWORD

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June 2016 Ali FAHMI

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ABBREVIATIONS

AI	: Artificial Intelligence
ANFIS	: Adaptive Neuro-Fuzzy Inference System
ANN	: Artificial Neural Network
BA	: Budget of Advertising
BN	: Bayesian Networks
CEM	: Coastal Engineering Manual
DAN2	: Dynamic Artificial Neural Network
DSS	: Decision Support System
FIS	: Fuzzy Inference System
FMCG	: Fast Moving Consumer Goods
GA	: Genetic Algorithm
GARCH	: Generalized Autoregressive Conditional Heteroskedasticity
gaussMF	: Gaussian Membership Function
gbellMF	: Bell-shaped Membership Function
GIS	: Geographic Information Systems
GRP	: Gross Rating Point
GSM	: Global System for Mobile
GUI	: Graphical User Interface
IM	: In Mind
ISE	: Istanbul Stock Exchange
KMO	: Kaiser-Meyer-Olkin
MF	: Membership Function
MLP	: Multiple Layer Perceptron
MSE	: Mean Square Error
NAZDAQ	: National Association of Securities Dealers Automated Quotations
NN	: Neural Network
NPD	: New Product Development
PCA	: Principle Component Analysis
RMSE	: Root Mean Square Error
SEM	: Structural Equation Modeling
SOV	: Share of Voice
SVM	: Support Vector Machine
TEPIX	: Tehran Exchange Price Index
TMA	: Total Market Advertising
trapMF	: Trapezoidal Membership Function
triMF	: Triangular Membership Function
TOM	: Top of Mind

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MODELLING THE EFFECTS OF BRAND IMAGE COMPONENTS ON ADVERTISING AWARENESS USING A NEURO-FUZZY SYSTEM

SUMMARY

Almost all the worldwide and nationwide companies utilize advertising to increase their sales volume and profit. These companies pay millions of dollars to reach consumers and announce their products or services. This forces companies to evaluate the advertising and check whether ads meet company's strategies. They need to evaluate the ads not only after announcement, but also before advertising, i.e. they can be one step ahead by predicting the future through artificial intelligence tools such as fuzzy systems and artificial neural networks.

The emergence of fuzzy logic and fuzzy sets has revolutionized the mathematics and engineering sciences. Fuzzy sets consider not only classical membership degrees, i.e. 0 and 1, but concern with all the degrees between zero and one. This enables fuzzy sets to mathematically represent linguistic variables and human judgment. It can deal with the uncertainty of decision maker's assessments and practically enhance decision making process. Rule based fuzzy systems basically apply fuzzy sets and process the inputs by IF-THEN rules to infer, and provide defuzzified outputs.

Neural network (NN) is a fast-growing branch of artificial intelligence, and simultaneously, it is widely used in different fields in order to deal with complex datasets. NN can be properly applied in estimation, clustering, compression, and filtering. The estimation ability of NN is highly needed to evaluate decisions before decision making moment. This would provide an infered knowledge beforehands, which is a vital need in today's turbulent market.

In this study, we propose to use a well-known combined neuro-fuzzy method, adaptive neuro-fuzzy inference system (ANFIS), to analyze advertising decision making. Although advertising data are highly complex and mixed with non-linearity, ANFIS is able to receive input data and estimate the output(s). Here, using dimension reduction method, 30 variables of brand image on advertising awareness reduced to 2 variables. Then, ANFIS creates fuzzy rules and trains the network using input data. This training ability of ANFIS leads to predict the advertising awareness outputs. In this study, we investigate three advertising awareness outputs, namely, top of mind, share of voice, and spontan.

In order to validate the ANFIS estimation, 30 percent of data are randomly splitted as the testing data and remained 70 percent are training data. The root mean square error (RMSE) graph of predicitons represent the validation of estimations. On the other hand, according to the predictions of outputs and measurements, the correlations

are calculated to check the validity of estimations. As an alternative method, we employ ANN to train the input data and predict the outputs. The comparison between the results of ANFIS and ANN shows higher correlation of ANFIS predictions and given data, which reveals that ANFIS outperforms ANN in prediction of advertising awareness data.

We finally created a graphical user interface (GUI) to support decision maker. This decision support system (DSS) equips a database, a modelbase with ANFIS and ANN methods, and a GUI. It can train the given data, and estimate the output and find the errors of estimation. This DSS can also depict the results of ANFIS and ANN simultaneously and allow the user to compare their prediction ability.

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ÖZET

Hemen hemen tüm dünya ve ülkeler çapında şirketler satış hacmini ve karını artırmak için reklamı kullanmaktadırlar. Bu şirketler tüketicilere ulaşmak ve ürünlerini veya hizmetlerini duyurmak için milyonlarca dolar para harcamaktadırlar. Şirketler reklamların değerlendirilmesi sürecinde ve stratejilerinin karşılığını almada büyük bir çaba gösterirler. Şirketler sadece reklamın duyurulmasından sonraki süreçte değil, aynı zamanda reklamın oluşturulmasından önceki süreçlerde de değerlendirme yapmaya ihtiyaçları vardır. Böylelikle şirketler bulanık sistemler veya yapay sinir ağları gibi yapay zeka araçları ile geleceği tahmin ederek bir adım önde olabilirler.

Bulanık mantık ve bulanık kümelerin ortaya çıkması matematik ve mühendislik bilimlerinde büyük bir devrim yarattı. Klasik kümelerde sadece sıfır ve bir değerleri dikkate alınıyor. Halbuki bulanık kümeler de ise sadece 0 ve 1 değerlerini değil, sıfırla birin arasındaki bütün değerleri göz önünde bulundurularak, her üye için üyelik derecesi belirleniyor. Bu kümeleri geliştiren bilim insanı, Zadeh, daha sonra bulanık kümeleri kullanarak dillsel değişkenlerin tanımını gelıştirdi. Bu değişkenler insanların değerlendirmelerini dilsel bir şekilde sağlamaktadırlar. Bu karar vericilerinin değerlendirilmelerindeki belirsizliklerle başa çıkılabilir ve pratik karar verme sürecini güçlendirebilir. Kural tabanlı bulanık sistemler temelde bulanık kümeleri uygularlar ve IF-THEN kuralları anlaması için girdileri işlerler ve defuzzify çıktıları sağlarlar.

Sinir ağları yapay zekanin hızla büyüyen bir dalıdır ve aynı zamanda, yaygın karmaşık veri setleri ile başa çıkmak için farklı alanlarda kullanılmaktadır. Yapay sinir ağları'nda (YSA) tahmin etmek, kümeleme yapmak, sıkıştırma veya filtreleme gibi yapılar uygulanabilir. YSA tahmin yeteneği karar verme anından daha önce kararları değerlendirmek için gereklidir. YSA, bugünün çalkantılı pazarında önemli bir ihtiyaç olan önceden yorumlanmış veya anlamlandırılmış bilgiyi sağlayacaktır.

Bu çalışmada, markaların tanılılırlığını analiz etmek için iyi bilinen bir birleşik nöro-bulanık bir yöntem ile adaptif bulanık sinir çıkarım sistemini (ANFİS) öneriyoruz. Reklam verileri yüksek oranda karmaşık ve doğrusal olmayan bir yapıya sahip olmasına rağmen, ANFİS ile bu yapıdaki girdilerle çıktı(ları) tahmin etmek gerçekleştirilebilir. Burada, boyut indirgeme yöntemiyle, reklam bilinci marka imajının 30 değişkenini 2 değişkene düşürüldü. Ardından, adaptif bulanık sinir çıkarım sistemi, bulanık kurallar oluşturarak ve giriş verileri kullanılarak oluşturduğu ağı eğitir. ANFIS Bu eğitim yeteneği ile reklam farkındalık çıktılarını tahmin eder. Bu çalışmada, üç reklam farkındalık çıktıları; yani akla ilk gelen marka (TOP), ses payı

(SOV), ve spontan araştırılmaktadır.

Adaptif bulanık sinir çıkarım sistemi, tahminini doğrulamak için, verilerin yüzde 30'i rastgele test verisi olarak parçaladık ve yüzde 70 veriyi de eğitim için kullandık. Tahminlerin kök ortalama kare hata grafikleri kestirimlerin doğrulanmasını yansıtmaktadır. Öte yandan, çıktıların ve ölçümlerin tahminlerine göre, korelasyonlar kestirimlerin geçerliliğini kontrol etmek için hesaplandı. Alternatif bir yöntem olarak, YSA da girdi verilerini eğiterek, çıktıların tahmininde kullandık. ANFIS ve YSA sonuçları arasındaki karşılaştırmada, ANFIS reklam farkındalık verileri tahmininde YSAnın geride olduğu ortaya çıkmıştır. Adaptif bulanık sinir çıkarım sistemi tahminleri verilen verilerin yüksek korelasyonunu göstermektedir.

Sonunda karar vericiyi desteklemek için bir grafik kullanıcı arayüzü oluşturuldu. Bu karar destek sistemi bir veritabanı, adaptif bulanık sinir çıkarım sistemi ve YSA yöntemleri ile bir model tabanlı ve bir arayüz olarak tasarlandı. Bu sistemle verilen verilerin eğitmini, çıktıların tahmini ve tahmin hataları görülebilir. Bu karar destek sistemde, eş zamanlı olarak adaptif bulanık sinir çıkarım sistemi ve YSA sonuçları görülebilir ve kullanıcıya tahminlerin değerlerinin karşılaştırılmasına imkan sağlanır.

1. INTRODUCTION

1.1 Introduction of the Problem

Advertising originates in the history of ancient civilizations such as Romans' paintings on the walls to announce gladiator fights, and sales announcements in Greece during golden age [1]. Nowadays, companies exploit modern tools such as social media to announce their activities and/or promote their products or services. Advertising nowadays contains a wide range of contents, from persuading people to purchase business products to educational messages and informing about healthcare services. These vast types of ads are transmitted every day in social media, television programs, streets, etc. and companies are searching for targeted audiences everywhere. So that, the advent of internet and social media has revolutionized the advertising formation. This structure of ads is more psychologically professional and more tempting than predecessors.

On the other hand, high population growth and huge markets like China and India broaden the advertising audiences. These increase the emergence of various ads, which are paid hundreds of million dollars to be advertised in different media and stick their brand image in people's mind. The huge expenses of advertising and subsequent financial transactions represent the crucial role of advertising in today's marketing management. In this regard, marketers need to plan to advertise their products and/or services. According to Lee and Johnson [2], in order for advertising planning, the advertising managers review the marketing strategies to comprehend the company's intentions, and then understand the role of advertising in the marketing mix. Advertisers then should perceive the current situation of the company, target market(s), short- and long-term marketing objectives, decisions on products' life cycle, marketing mix, and their position in the market.

This leads to clearly determine the advertising objectives of the company, and identify the precision and measurability of advertising. Therefore, advertiser would be able to evaluate advertising success at the end of the advertising campaign, and assess whether the advertising objectives have been met or not.

1.2 Our Suggestion

Marketers should evaluate the company's advertising and assess the effects of ads on people's mind. The more people remember an ad and the long period of time it lasts in their minds, the more successful ad has been announced.

Companies usually evaluate their advertising through monetary criteria such as profit, or sales volume. However, other criteria may better demonstrate the real effect of advertising on people in long term horizon. For this reason, while the measurement of people's perception is difficult, companies attempt to catch brand awareness or product awareness by questioning individuals.

Since advertising and then evaluation of advertising is a time consuming process, advertisers need to be one step beyond the trial and error, i.e. they should be able to predict the effect of a special advertising with particular advertising message. The prediction ability of artificial intelligence (AI) tools such as fuzzy systems or artificial neural networks (ANN) can support advertiser. Using recorded advertising data, these intelligent systems can estimate the effects of different types of advertising. This can elucidate the invisible side of advertising awareness and empower decision makers to estimate the consequences of their decisions. In this study, we propose to apply adaptive neuro-fuzzy inference system (ANFIS), which is a well-known combination of fuzzy inference systems (FIS) and ANN. ANFIS is an admitted tool to deal with non-linear and chaotic data, and it is broadly used to predict complex concepts.

1.3 Summary of Future Sections

This thesis is structured as follows: section 2 devotes to the advertising, advertising awareness and the influence of advertising on the brand image. The history of advertising and customer relationship, as well as the relevant concepts of advertising evaluation are presented in this section. In the section 3, the methodologies including fuzzy sets, fuzzy rules, ANN, and ANFIS will be described. Section 4 contains the application of the proposed model, details about data. In this section, ANN and

ANFIS are compared, and the proposed support system is presented. Using different measurements of advertising awareness, different estimation of the model, root mean square error (RMSE), and testing data errors are also provided in section 4. Finally, section 5 is devoted to the conclusion and suggested future works.

2. ADVERTISING AWARENESS

Advertising is a part of the broad activities of marketing department. It is defined as "any paid form of non-personal presentation and promotion of ideas, goods, or services by an identified sponsor" [1] (p.458). Most of the business companies, as well as not-for-profit organizations, professionals, and social agencies use advertising to promote their products or services.

According to Kotler and Armstrong [1], there are four main decisions in developing an advertisement program, namely, setting advertising objectives, setting the advertising budget, developing advertising strategy, and evaluating advertising campaigns. Advertising objective refers to a specific communication task to be achieved with a determined target audience in a determined period of time. Advertisement can embed different objectives such as information, persuade, and remind. Based on these objectives, advertising can be classified as informative advertising, persuasive advertising, and reminder advertising. Considering the advertising objectives, the budget will be allocated to advertise each product or service. In order to accomplish the advertising objectives, advertising strategy should be developed. Advertising strategy deals with two main responsibilities: creating advertising messages and selecting advertising media. Ads should be created in a way that affect audiences, and should be transmitted by appropriate media. Finally, the advertisement should be evaluated to control if the company reach the determined advertising objectives.

Successful developing of advertising program, i.e. setting objective, budget, strategy, and evaluation of advertising can guarantee advertising awareness by the majority of target audiences. This can also approach marketing department to the planned goals through creating an impressive awareness of advertisement followed by a memorable awareness of product.

2.1 Brand Image

Brand image is a set of perceptual beliefs about a brand's attribute, benefit, and attitude associations, which are frequently seen as the basis for an overall evaluation of, or attitude toward, the brand [3]. Brand image is a holistic construct formed from a gestalt of all the brand associations related to the brand. It is different from brand attitude, which is consumers' overall evaluation of the brand. However, brand attitude is conceptualized as just one of the various associations used in the formation of the brand image. Aaker [4] defines brand equity as a behaviorally oriented construct influenced by a consumer's image and attitude of the behavior's object. As shown in below, brand image and brand attitude impact brand equity, and brand image consists of brand associations, brand loyalty, brand awareness, perceived quality, and other brand assets [3, 4].

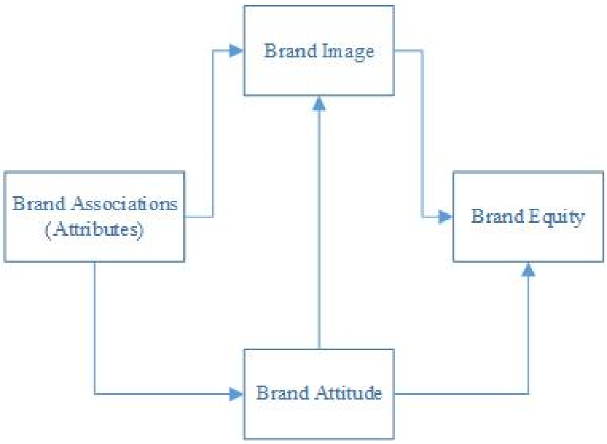


Figure 2.1 : Brand associations, brand image, brand attitude, and brand equity.

Considering psychological theories, Kotler and Armstrong [1] stated four main factors that affect a particular person's purchase decision including motivation, perception, learning, and beliefs and attitudes. Motivation points out the need that sufficiently press the person to buy the product or service and satisfy the need. A motivated person perceives the process of selection, organizing, and interpreting information to form a meaning picture of the world. This perception leads to changes in an individual's behavior and learn from experiences. Lastly, the learning process terminates to form beliefs and attitudes.

Marketers consider the beliefs of people to supply their needed products or services. They firstly create a brand which is a name, term, sign, symbol, or a combination of these elements to introduce the product or service [1], and then develop an influential image of the brand that affects buying behavior. This brand image is introduced by Ogilvy [5] which considers personalities for the brands that and stick to thm. This refers to the total personality of a particular brand, rather than any trivial product difference, which decides its ultimate position in the market.

2.2 Advertising and Brand Image

As mentioned before, most of business companies use advertising to promote their products or services. As mentioned before, a crucial decision in developing the advertisement is the evaluation of advertising campaigns. Additionally, according to Kotler and Armstrong [1], advertising strategy consists of creating message and selecting appropriate media.

The primary step to create an effective advertising strategy is to prepare a message strategy. This message is a communication way to consumers, and it should get consumers to think about or react to the product or company in advertiser's determined way [1]. Secondly, selecting advertising media denotes to determining reach, frequency, and impact of advertisement. The marketing department is then responsible to choose suitable media types and select specific media vehicles, as well as media timing. The reaction of people happens only if they believe they will benefit from the presented product or service. The message of advertisement tends to plain, straightforward outlines of benefits and positioning points that the advertiser wants to stress [1].

Since advertising is often the largest single cost in marketing budget, companies are giving weight to advertising research. Lee and Johnson [2] divided advertising research into two types: media research and message research. The first one, media research, addresses the information about the circulation of newspapers and magazines, and broadcast coverage of television and radio. A variety of resource materials are available to advertisers for determining the potential audience size for specific media vehicles.

The latter, message research, considers the effectiveness of advertising messages in communicating to people. Media research analyzes how well those messages influence people's behavior. Measuring advertising effectiveness and the return on advertising investment has become a crucial subject for most companies which are challenging in the current competitive economic environment. In advertising effectiveness, advertising researchers measure the influencing attitudes, achieving awareness, conveying copy points, creating emotional responses, and affecting purchase choices. Accordingly, there are five different forms of responding to ads, namely, measures of recognition and recall, measures of emotions, measures of physiological arousal, measures of persuasion, and measures of sales response [2].

2.3 Advertising Awareness Measurement

As a major decision in developing an advertisement program, advertising campaign should be evaluated by the marketing department. But, since advertising is the cornerstone of different marketing strategies and is not only the defining element of the marketing mix, advertising evaluation is a literally difficult and expensive process [6].

Advertising can be evaluated by two main advertising results, the sales and profit effects, and the communication effects of advertising [1]. Advertisers can measure the sales and profit effects of advertising by comparing post-advertising sales and profits with pre-advertising sales and profits. However, it is difficult to find the appropriate measurement time before, and especially after advertising. This means that advertiser should estimate the impression period of post-advertising.

On the other hand, after an advertising is run, it can be measured by observation of consumers' recall and/or product awareness. Similar to the sales and profit effects measurement, the effects of pre-advertising and post-advertising communications will reveal the advertising awareness. This measurement requires the link between consumer, customer, and public to the marketer. The stream of information can identify and reveal marketing opportunities, which leads to generating appropriate marketing actions. Hence, although it is not easy to track the incremental sales associated with advertising campaigns, marketers have developed some marketing metrics such as top of mind, share of voice, and spontan, which are described as follows:

2.3.1 Top of mind

Top of mind or TOM measures the advertising awareness, which represents the first brand that comes to mind when a customer is asked an unprompted question about a category. TOM is calculated as the percentage of customers for whom a given brand is top of mind can be measured [6]. This will represent the influence of the transmitted advertising, i.e. if an advertising successfully received to audiences, it should stick in their mind. Thus, they should remember the advertised brand when they are questioned about the most prominent brand of a particular sector.

2.3.2 Share of voice

Share of voice or SOV is another measurement factor of advertising awareness. SOV refers to the intensity of advertising for a particular brand compared with all other brands of a given product. It is generally measured in dollars, and can be calculated at a company level, brand level, or product level [6, 7].

SOV is the amount of advertising of a company compared to that of its competitors, i.e. SOV quantifies the advertising presence that a specific brand exploits [6]. Thus, considering the budget of advertising (BA) and total market advertising (TMA) in dollars or the number of respondents, the percentage of SOV is calculated as follows:

$$SOV(\%) = \frac{BA(\$,\#)}{TMA(\$,\#)} \tag{2.1}$$

SOV can display the percentage of targeted people who remember the most prosperous advertising. The more successful and more impressive advertising, the more memorial and the higher share of voice.

2.3.3 Spontan

Spontan refers to rememberance of a particular brand, i.e. when you ask people about banking corporations, the percentage of people who mention a particular brand is the spontan of that brand. The difference between TOM and spontan is that TOM concerns with the first brand mentioned by the questioned person, but spontan regards the entire memorized brands either the first or second or even the last.

2.4 Literature Survey

The major problem with most of real world data and time series is the non-linearity and complexity of dataset. Compared with statistical analysis like regression, ANN offers many advantages over these conventional approaches [8]. Artificial neural network (ANN) is a well-known method to deal with incomplete data, non-linear data and outliers and analyzing noisy data [8]. This interaction ability of neural network catches many researchers from different disciplines to apply neural networks. Most of the previous studies have been applied ANFIS and ANN from water management [9–11] to medical applications [12].

ANFIS is also broadly applied in management from stock market prediction [13–21] to sales forecasting [22–27]. In civil management and water management, Karimnezhad, Etemad-Shahidi, and Mousavi [28] applied ANFIS and coastal engineering manual (CEM) for wave prediction. Comparing the results, the prediction capability of ANFIS is superior to CEM's. Mahjoobi et al. [29] compared ANN, fuzzy inference system (FIS) and ANFIS in wave prediction of Lake Ontario, and found similar errors in different methods, but the results of ANFIS were more accurate than the results of FIS and ANN. Similarly, Malekmohamadi et al. [30] applied support Vector Machine (SVM), Bayesian Networks (BN), ANN, and Adaptive Neuro-Fuzzy Inference System (ANFIS) to evaluate the wave height using wind data, and found the best results in ANN estimations. In order to estimate daily evaporation of south western Iran, Shiri and Kisi [9] applied genetic algorithm (GA) using daily climate variables, i.e. air temperature, sunshine hours, wind speed, and relative humidity. The performance of their model was measured by correlation coefficient, RMSE, coefficient of residual mass, and scattered index. They therefore assessed the ability of GA model by neuro-fuzzy and artificial neural networks, which GA outperformed both of these methods.

Shiri et al. [10] developed an ANFIS model to estimate the reference evapotranspiration using data from Spanish humid (Basque Country) and non-humid (Valencia) regions to train the model, and used Iranian humid and non-humid stations to test the model. In order to compare ANFIS and ANN, Khaki, Yusoff, and Islami [11] evaluated the water quality parameters from five sampling sattions in Malasia. The performance of both methods was measured by the correlation coefficient and mean squared error (MSE), and finally ANFIS had lower computational complexities and trained faster that ANN. In another study, sediment transport was analyzed using ANFIS and ANN [31]. Based on the results of R squared and RMSE, ANFIS outperformed ANN in most of the cases.

There are many applications of ANFIS in prediction of stock markets all over the world. By integrating artificial neural network and fuzzy neural network, Kuo, Chen, and Hwang [13] developed a decision support system for stock trading. Atsalakis and Valavanis [14] employed ANFIS to forecast short-term trends of Athens and New York stock markets. They chose Gaussian-2 shaped membership functions over bell shaped Gaussian and triangular ones to fuzzify the system inputs, and found the lowest RMSE. Esfahanipour and Aghamiri [15] applied neuro-fuzzy inference adopted on a Tagaki-Sugeno-Kang to predict stock price and tested on the Tehran Stock Exchange Index (TEPIX). They have used fuzzy C-Mean clustering method to identify the number of fuzzy rules.

Using ANFIS, Boyacioglu and Avci [16] predicted stock market return of Istanbul Stock Exchange (ISE). Ansari et al. [17] used ANFIS to predict NASDAQ stock market index. This neuro-fuzzy system implemented hybrid least-square method and the Back-propagation gradient descent methods to train the fuzzy interface system (FIS). Esfahanipour and Mardani [18] predicted Tehran stock exchange price index using multi-layer perceptron ANN and compared with ANFIS and fuzzy C-Means. Based on the prediction results, ANFIS outperformed ANN model of multi-layer perceptron. Guresen, Kayakutlu, and Daim [19] applied multi-layer perceptron (MLP), dynamic artificial neural network (DAN2), and also hybrid neural networks which use generalized autoregressive conditional heteroscedasticity (GARCH) to predict NASDAQ Stock Exchange index. Svalina et al. [20] applied neuro-fuzzy inference system to predict Zagreb Stock Exchange Crobex index. And, recently, Qiu, Song, and Akagi [21] used ANN to predict the return of the Japanese Nikkei 225 index using GA and simulated annealing to improve the prediction accuracy of ANN.

Kuo and Xue [22] and Kuo and Xue [23] implemented a decision support system and employed fuzzy ANN and ANN to forecast sales volume. Using fuzzy Delphi method to collect the fuzzy inputs and outputs, fuzzy IF-THEN rules, achieved from marketing experts, were trained and then integrated with the forecast from ANN. Kuo [24] proposed a fuzzy ANN to train fuzzy IF-THEN rules to forecast sales data. This system were initialized with generated weights by GA. Then, based on this integrated model, Kuo, Chen, and Hwang [13] developed a decision support system for stock trading. Kuo, Wu, and Wang [25], then, boosted the integrated ANN and fuzzy ANN system by adding fuzzy weight elimination. Efendigil, Onut, and Kahraman [26] employed ANN and ANFIS to forecast demand of a multi-level supply chain, and the results of ANFIS were closer to the actual values. Dwivedi, Niranjan, and Sahu [27] applied ANFIS and ANN to forecast the automobile sales, which resulted ANFIS outperformance.

ANFIS is also widely used in different branches of management sciences. DeTienne and DeTienne [8] believed that marketing studies investigating customer preferences and customer satisfaction could benefit from the ability of ANNs to discover relationships and make predictions using inputs that can't be organized into a pre-specified model. In this regard, to estimate the value innovation and the effects of quality of new product development (NPD) process on NPD performance, Ho and Tsai [32] compared the performance of ANFIS and structural equation modeling (SEM). The results cleared that ANFIS has superior forecasting ability to SEM, due to effective explanation of nonlinear relationships between NPD process quality and NPD performance. In churn management, Karahoca and Karahoca [33] investigated the global service and mobile communication (GSM). They firstly clustered input data by x-means and fuzzy C-Means, then, used ANFIS for prediction. Lin et al. [34] states that forecasting methods are classified into two groups: linear and nonlinear. The first one, linear forecasting methods, such as least squares analysis or correlation methods are useful, but sometimes fail to forecast nonlinear time series. However, nonlinear forecasting models such as ANFIS, Bayesian model, support vector regression, etc. provide effective performance in nonlinear situation. Lin et al. also provide a geographic information system (GIS) to facilitate decision making process by comparing different performance.

Although there are various studies which considered neural network to investigate various managerial problems, neural network rarely applied in marketing, especially advertising evaluation. Using neural network, TOM and in mind (IM) factors are predicted to measure the effect of advertising on the Swedish car industry including 9 well-known brands [35]. Johansson et al. [36] also used neural network and rule extraction to estimate TOM and IM of Swedish travel companies. But, to our knowledge, there are no more similar studies which employed ANFIS or ANN in advertising evaluation.

As you see in literatures above, ANFIS or ANN or other estimation methods are not absolutely superior to each other. However, each of these methods outperform the other in different studies. On the other hand, as mentioned in Section 2.3., advertising is the cornerstone of marketing strategies, and implies the difficulty of advertising evaluation [6]. This demonstrate the significance and complexity of the elements of advertising evaluation, which can unveil non-linear relationships between the elements. Consequently, according to the abilities of AI methods such as fuzzy systems or ANN in dealing with non-linear and complex data, these methods can provide practical and useful outcomes in advertising evaluation problems. In this study, we apply ANFIS in advertising assessment and estimate the future brand awareness of considered companies using the prediction ability of ANFIS method. We then establish ANN to predict the advertising awareness, and compare the estimations of ANFIS and ANN.

3. METHODOLOGY

In this chapter, fuzzy sets, fuzzy systems, artificial neural networks, and artificial neuro-fuzzy inference systems (ANFIS) method are described shortly, as the preliminaries for the applications in the next section.

3.1 Fuzzy Sets

Famous mathematician, Wilhelm Leibniz, believed that “if we could find characters or signs appropriate for expressing all our thoughts as definitely and as exactly as arithmetic expresses numbers or geometric analysis expresses lines, we could in all subjects, in so far as they are amenable to reasoning, accomplish what is done in arithmetic and geometry.” Ross [37] states that the most powerful form of conveying information may be natural language that humans possess for solving or reasoning of any given problem. By rising of the utility of fuzzy logic, Leibniz’s belief and the power of human expression became realized in today’s mathematical paradigms. The need for expressing linguistic variables using the precepts of mathematics is quite well established. Zadeh [38] defines a linguistic variable as a variable which values are words or sentences in a natural or artificial language. With these definitions and foundations, we are now in a position to establish a formal model of linguistics using fuzzy sets.

Ross [37] defined a specific atomic term in the universe of natural language, X, as element α, and we define a fuzzy set $\widetilde{A}$ in the universe of interpretations, or meanings, Y, as a specific meaning for the term α. Then, natural language can be expressed as a mapping $\widetilde{M}$ from a set of atomic terms in X to a corresponding set of interpretations defined on universe Y. Each atomic term α in X corresponds to a fuzzy set $\widetilde{A}$ in Y, which is the “interpretation” of α. This mapping, which can be denoted $\widetilde{M}(\alpha,\widetilde{A})$, is shown schematically in Figure 3.1. The fuzzy set $\widetilde{A}$ represents the fuzziness in the mapping between an atomic term and its interpretation, and can be denoted by the membership function, $\mu_{\widetilde{M}}(\alpha, y)$ or more simply by

$$\mu_{\widetilde{M}}(\alpha, y) = \mu_{\widetilde{M}}(y) \tag{3.1}$$

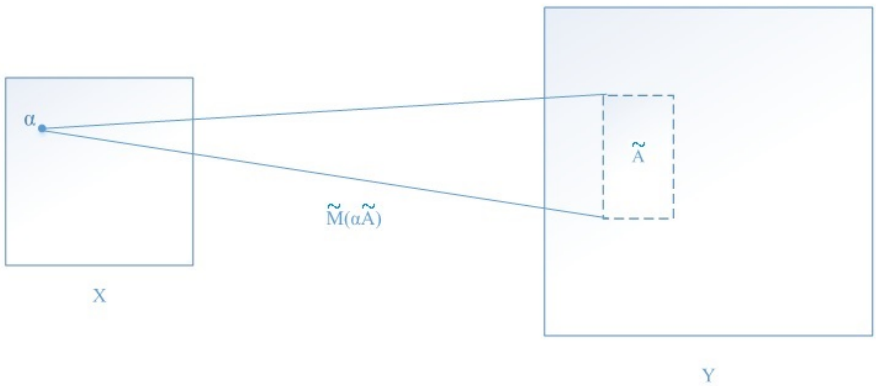


Figure 3.1 : Mapping of a linguistic atom α to a cognitive interpretation $\widetilde{A}$.

3.1.1 Fuzzy Rules

Each organization exploits experts and their latent knowledge to remain in the business. Negnevisky [39] defined knowledge as "a theoretical or practical understanding of a subject or a domain". The thinking power of human is a mental process and the outcome is subjective. The thoughts of an expert are also internal perceptions, which are difficult to be expressed in the form of algorithms [39].

In the field of artificial intelligence (machine intelligence) there are various ways to represent knowledge. Perhaps the most common way to represent human knowledge is to form it into natural language expressions of the type

IF premise (antecedent), THEN conclusion (consequent)

Expression above is called the IF–THEN rule-based form, which is genrally referred to as the deductive form. It typically expresses an inference such that if we know a fact (premise, hypothesis, antecedent), then we can infer, or derive, another fact called a conclusion (consequent). This form of knowledge representation, characterized as shallow knowledge, is quite appropriate in the context of linguistics because it expresses human empirical and heuristic knowledge in our own language of communication.

These rules are based on natural language representations and models, which are themselves based on fuzzy sets and fuzzy logic. The fuzzy level of understanding and describing a complex system is expressed in the form of a set of restrictions on the output based on certain conditions of the input. Conjunctions or disjunctions like "and", "or", and/or "else" are the restrictions of rules that connect different linguistic expressions to create more complex premise. They are are generally modeled by fuzzy sets and relations. These advanced version of IF-THEN rules can be equipped multiple antecedents and/or uncommonly multiple consequents. These antecedents are joined by AND (conjunction), OR (disjunction) or a combination of both [39].

IF <antecedent 1> AND <antecedent 2> AND < antecedent 3> THEN <consequent>

IF <antecedent 1> OR <antecedent 2> OR <antecedent 3> THEN <consequent>

Since most of the rule-based systems deal with fuzzy rules, multiple fuzzy rules should be aggregated. This process is known as the aggregation of fuzzy rules, and two regular aggregations are as follows [40]:

Conjunctive system of rules like $y = y^1$ and y^2 and ... and y^r which is defined by the membership function (MF) as follows:

$$\mu_y(y) = \min(\mu_{y^1}(y), \mu_{y^2}(y), ..., \mu_{y^n}(y)) \tag{3.2}$$

Disjunctive system of rulese like $y = y^1$ or y^2 or ... or y^r which is is defined by MFs as follows:

$$\mu_y(y) = \max(\mu_{y^1}(y), \mu_{y^2}(y), ..., \mu_{y^n}(y)) \tag{3.3}$$

3.1.2 Artificial Neural Network

Artificial neural network (ANN) is an attempt of modeling human cognitive system. ANN is a technology that has been mainly used for prediction, clustering, classification, and alerting to abnormal patterns [41]. ANNs can identify patterns between the dependent and independent variables in datasets. This pattern recognition as well as optimization of large-scale problems are the principal strengths of ANNs [8, 42]. ANNs can deal effectively with data discontinuities, outliers, missing data and even nonlinear transformations.

$$u_k = \sum_{j=1}^{p} w_{kj} x_j \quad \forall j = 1, 2, ..., p \tag{3.4}$$

$$y_k = \varphi(u_k - \theta_j) \tag{3.5}$$

where x represents the input signals and w represents the synaptic weights of neuron k. y_k is the output signal of the neuron, and φ is the activation function. u_k is the linear combiner output and θ_j denotes the threshold [41].

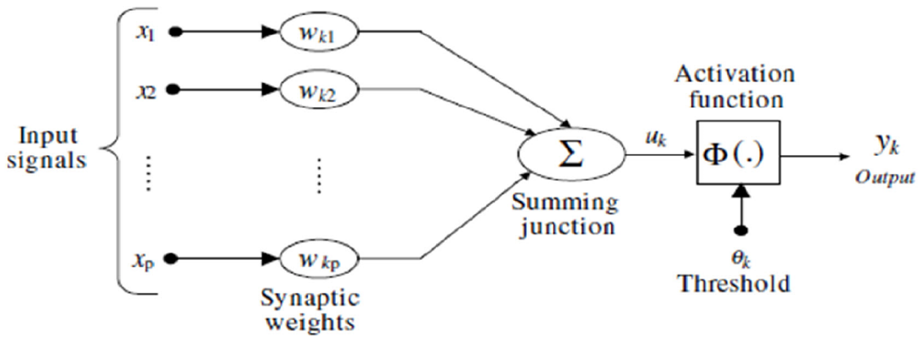


Figure 3.2 : Non-linear model of a neuron.

In order to introduce the non-linearity characteristics into the ANN model, a transfer function is used. Activation function can be either linear or nonlinear function, and limits the value of output neuron between 0 and 1, or between -1 and 1. Linear activation function is like a product of each layer's weight matrices. Sigmoid or logistic function is the most chosen function for back-propagation. It is able to help the generalization of learning characteristics to yield models with improved accuracy [43].

$$\varphi(x) = \frac{1}{1+e^{-x}} \tag{3.6}$$

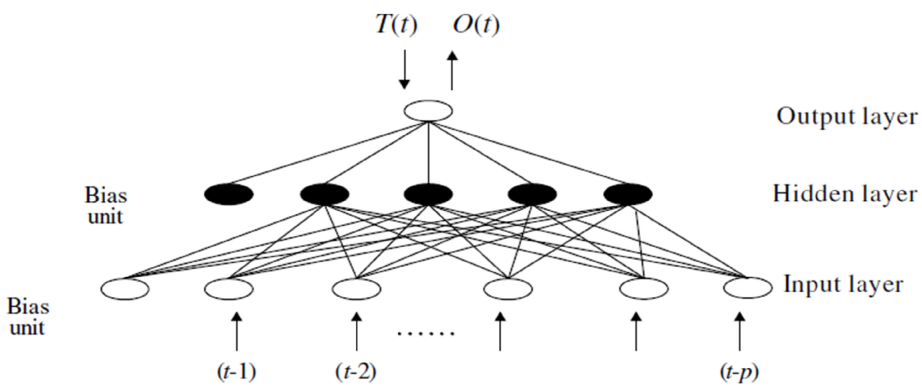


Figure 3.3 : The ANN structure.

There are usually a number of hidden layers between these two layers. The hidden layer of an ANN model acts as a black box to link the relationship between input and output [43]. According to some literature studies, the maximum number of hidden layer nodes can be (1) 2n + 1, where n is the number of nodes in the input layer, (2) 75% of the quantity of input nodes, or (3) 50% of the quantity of input and output nodes [44–46].

The main advantage of ANN is the learning capability using previous recorded data. Learning capability of ANN is in two ways supervised and unsupervised learning. Supervised learning is used when the dataset has a target output value. Back-propagation is the most applied method to adjust the weights in supervised training of ANN. The concept of back-propagation learning is a simple learning method, i.e. the subtraction of the actual and target outputs provides the error through backward propagation, and the weight values are adjusted to minimize the value of error.

Accordingly, unsupervised learning is used when the training dataset lacks target output values. Unsupervised training makes weight adjustments with respect to correlations in the input variables, which are really both input and target variables [47]. Because unsupervised networks focus only on the input values in a data-set, the output layer is not used in training process. Yet output node is only used during interpretation of the results [48].

There are three adjusting factors to control the learning rate of ANN, namely, learning rate coefficient, momentum, and the exit conditions. Learning coefficient manages the rate of learning by changing the weights over time. Momentom factor controls how much iteration an error adjustment persists [26]. High momentum cripples network adaptability. On the other hand, low momentum causes weight oscillation and instability, preventing the learning process of network. Momentum factor is kept close to and less than one, in order to reach the stable backpropagation. DeTienne and DeTienne [8] believe that a small momentum factor is optimum during training, whereas it should be larger toward the end of training. Exit condition also points out the stopping rule of ANN to control the termination of the training [43].

The training process will stop when all patterns are classified correctly and selected a range of accuracy. This is called over-fitting or over-training. As mentioned above, the objective function of ANN is the minimization of error. The squared error is represented by and calculated as follows:

$$E = \sum (t_p - y_p)^2 \tag{3.7}$$

To generalize the NN architecture, a validation data set is applied to check the degree of generalization of the trained model and is evaluated whether the output is close enough for an input [43].

3.1.3 Adaptive Neuro-Fuzzy Inference System

An inference system employing fuzzy if-then rules can model the human knowledge in the form of qualitative inputs. ANFIS can conduct reasoning process without employing precise quantitative analyses [49]. Therefore, while input-output relationships are not explicitly given in ANN, these relationships are represented explicitly in the form of if-then rules in neuro-fuzzy systems.

Neuro-fuzzy modelling has been recognized as a powerful prediction tool, due to combining quantitative information, like data, and qualitative information, like expert's knowledge, to facilitate the effective development of models. Hence, on the contrary of some complicated methods which are notoriously recognized as "black box" methods like neural networks, most of the neuro-fuzzy models can be better used to explain solutions to users [50, 51]. Assume the fuzzy inference system has two inputs x and y and one output z, and rule base has two fuzzy rules of Takagi and Sugeno's type [52].

If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$
If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$

where A_i and B_i are the fuzzy sets, f_i is the output set within the fuzzy region specified by the fuzzy rule p_i and q_i and r_i are the design parameters that are determined during the training process.

ANFIS has a five layer feed forward neural network. The node functions in the same layer are of the same function family as described below [49]:

Layer 1. Every node i in this layer is a square node with a node function

$$O_i^1 = \mu_{A_i}(x) \quad i = 1, 2 \tag{3.8}$$

where x denotes the input to node i, and A_i is the linguistic label like small, large, etc. O_i is the membership function of A_i and it specifies the degree to which the given

x satisfies the quantifier A_i. The membership function can be triangular, trapezoidal, bell-shaped, Gaussian, etc.

$$O_i^1 = \mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i}} \tag{3.9}$$

where a_i, b_i, c_i is the parameter set of the bell-shaped membership function.

Layer 2. Every node in this layer is a circle node labeled II which multiplies the incoming signals and sends the product out. For instance,

$$O_i^2 = \omega_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \quad i = 1, 2 \tag{3.10}$$

Each node output represents the firing strength of a rule.

Layer 3. Every node in this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \widetilde{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2} \quad i = 1, 2 \tag{3.11}$$

For convenience, the output of this layer is called normalized firing strengths.

Layer 4. Every node i in this layer is a square node with a node function

$$O_i^4 = \widetilde{\omega}_i f_i = \widetilde{\omega}(p_i x + q_i y + r_i) \tag{3.12}$$

where p_i, q_i, r_i is the parameter set which are referred to as consequent parameters.

Layer 5. The single node of this layer calculates the overall output as a summation of all incoming signals as follows:

$$O_i^5 = \sum \widetilde{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \tag{3.13}$$

In ANFIS structure, the premise and consequent parameters should be noted as important factors for the learning algorithm in which each parameter is utilized to calculate the output data of the training data. The premise part of a rule defines a subspace, while the consequent part specifies the output within this fuzzy subspace [49].

It is observed that given the values of premise parameters, the overall output can be expressed as linear combinations of the consequent parameters. More precisely, the output of the ANFIS model can be written as in Jang [49]:

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 \tag{3.14}$$

$$f = \widetilde{\omega}_1 f_1 + \widetilde{\omega}_2 f_2 \tag{3.15}$$

Using fuzzy if-then rules and Eq. (3.13), Eq. (3.14) will be yield

$$f = \widetilde{\omega}_1 (p_1 x + q_1 y + r_1) + \widetilde{\omega}_2 (p_2 x + q_2 y + r_2) \tag{3.16}$$

After arrangement, Eq. (3.17) equals

$$f = (\widetilde{\omega}_1 x) p_1 + (\widetilde{\omega}_1 y) q_1 + (\widetilde{\omega}_1) r_1 + (\widetilde{\omega}_2 x) p_2 + (\widetilde{\omega}_2 y) q_2 + (\widetilde{\omega}_2) r_2 \tag{3.17}$$

The hybrid algorithm used in ANFIS structure consists of the least squares method and the back-propagation gradient descent method for training FIS membership function parameters to emulate a given training data [53].

The hybrid learning algorithm of ANFIS has both forward and backward pass. The forward pass uses the least squares method to find the optimal parameters of consequent with fixed premise parameters. Then, backward pass applies gradient descent method to adjust optimally the parameters of premise corresponding to the fuzzy sets in the input domain [26].

The output of ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back-propagation algorithm.

One of the most commonly used approaches to validate neural networks is data splitting, i.e. data should be divided into three sets: train, test, and check. This method usually splits the dataset into 70%, 15%, and 15% sub-sets randomly, which form the training data set, testing data set, and checking set, respectively.

4. MODEL ESTIMATIONS

4.1 Proposed Model

In this study, we applied ANFIS to evaluate the advertising awareness data of major Turkish companies from different sectors. As discussed in section 2.3, we considered TOM, SOV, and spontan as the advertising awareness metrics, and predict their future values using AI tools.

4.2 Data and Application

The dataset consists of the results of a field study on advertising awareness, which is gathered during 21 months, from the January 2014 to September 2015. The questionnaire covered 30 questions about advertising effects, which are presented in Table A.1 in Appendix A.3. The questions reveal people's awareness on the advertising of 15 reputable Turkish brands, which cannot be mentioned here because of confidentiality of their advertising information.

Table 4.1 : Kaiser-Meyer-Olkin (KMO) and Bartlett's test.

KMO Measure of Sampling Adequacy.		**0.979**
Bartlett's Test of Sphericity	Approx. Chi-Square	13665.883
	df	435
	Sig.	**0.000**

Table 4.2 : Total variance explained by principal Component Analysis (PCA) of given inputs.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**21.667**	72.223	72.223	21.667	72.223	72.223	15.925	53.083	53.083
2	**2.338**	7.793	80.016	2.338	7.793	80.016	8.080	26.933	**80.016**
3	0.724	2.414	82.431						
4	0.610	2.033	84.464						
5	0.439	1.464	85.928						
6	0.356	1.186	87.114						
7	0.347	1.157	88.271						
8	0.305	1.018	89.289						
9	0.268	0.894	90.183						
10	0.249	0.830	91.013						
11	0.228	0.762	91.774						
12	0.218	0.726	92.501						
13	0.202	0.674	93.174						
14	0.194	0.647	93.821						
15	0.177	0.590	94.412						
16	0.170	0.568	94.980						
17	0.156	0.519	95.498						
18	0.143	0.476	95.974						
19	0.134	0.448	96.422						
20	0.130	0.434	96.856						
21	0.124	0.413	97.269						
22	0.113	0.377	97.646						
23	0.108	0.359	98.005						
24	0.104	0.345	98.350						
25	0.096	0.320	98.670						
26	0.092	0.307	98.977						
27	0.088	0.292	99.269						
28	0.081	0.272	99.541						
29	0.071	0.237	99.777						
30	0.067	0.223	100.000						

Using the questionnaire results as well as gross rating point (GRP), i.e. the advertising costs of a certain company in particular period of time, we formed the input set of ANFIS consisting 31 elements. TOM, SOV, and Spontan were measured, and we utilized them as three different outputs of ANFIS. Since running of ANFIS with 31 input variables is almost impossible, we applied PCA which its results are presented in Tables 4.1 and 4.2.

As you see in Table 4.1, KMO measure of sampling adequacy is 0.979 which is greater than 0.9, so the sample size is marvelous. Since Bartlett's test of Sphericity is 0.000, which is less than 0.005, null hypothesis is rejected and correlation matrix is not identity matrix, so there would be correlations between the variables. As represented in Table 4.2, two components reach eigenvalues greater than 1, and can explain more than 80 percent of total variance, which is a very good result. Consequently, PCA decreased the number of input variables from 30 to 2. We used these two components along with GRP as the inputs of ANFIS, and as mentioned before, considered TOM, SOV, and Spontan variables as output, separately.

Using these input and output variables, neuro-fuzzy method applied to find the least test error to find the most appropriate fuzzy MF and the number of MFs in each fuzzy envelope. Considered fuzzy MFs include triangular-shaped-built-in MF (triMF), trapezoidal-shaped-built-in MF (trapMF), generalized bell-shaped built-in MF (gbellMF), and gaussian curve built-in MF (gaussMF), with 3, 5, and 7 MFs. Tables 4.3, 4.4, and 4.5 represent the errors of neuro-fuzzy predictions for all data, companies which produce fast moving consumer goods (FMCG), and non-FMCG datasets, respectively.

Since the data of homogeneous companies can be predicted properly, we classified the companies and their products into fast moving cosumer goods (FMCG) and non-FMCG. Tables 4.4 and 4.5 also present the errors of neuro-fuzzy predictions of FMCG and non-FMCG datasets, respectively.

As shown in Table 4.3, considering all data, the minimum test errors are 0.042, 0.037, and 0.022 for TOM, SOV, and spontan, respectively. So, the first two ones are bell MFs and the last one is a trapezoidal MF, all with 3 functions. According to Table 4.4, the minimum test errors of ANFIS using FMCG dataset are 0.048, 0.040, and

Table 4.3 : Training and test errors using all data.

Output Type			Constant		Linear	
	MF Type	Number of MFs	Train Error	Test Error	Train Error	Test Error
TOM	triMF	3	0.029	0.080	0.027	0.413
		5	0.027	0.08	0.239	12.051
		7	0.024	0.392	0.011	0.08
	trapMF	3	0.03	0.063	0.027	0.093
		5	0.027	0.055	0.024	0.416
		7	0.024	0.07	0.014	0.401
	gbellMF	3	0.03	**0.042**	0.027	0.934
		5	0.025	2.565	0.226	575.706
		7	0.02	0.545	0.015	592.89
	gaussMF	3	0.029	0.048	0.026	0.239
		5	0.026	0.509	0.264	531.861
		7	0.019	2.137	0.009	527.948
SOV	triMF	3	0.016	0.042	0.014	0.451
		5	0.01	0.88	0.007	4.633
		7	0.005	0.191	0.003	1.964
	trapMF	3	0.026	0.04	0.012	0.101
		5	0.017	0.100	0.011	0.064
		7	0.013	0.055	0.003	0.24
	gbellMF	3	0.018	**0.037**	0.01	2.198
		5	0.013	0.385	0.202	93.031
		7	0.007	0.54	0.108	249.843
	gaussMF	3	0.017	0.043	0.01	0.658
		5	0.0108	0.149	0.019	332.793
		7	0.006	0.209	0.0088	110.96
Spontan	triMF	3	0.012	0.033	0.009	0.170
		5	0.008	0.052	0.003	29.478
		7	0.005	0.070	0.0021	7.685
	trapMF	3	0.013	**0.022**	0.010	0.033
		5	0.010	0.037	0.0077	0.102
		7	0.008	0.030	0.003	0.072
	gbellMF	3	0.013	0.023	0.008	0.762
		5	0.007	0.356	0.075	129.249
		7	0.005	0.330	0.002	50.583
	gaussMF	3	0.012	0.028	0.007	0.503
		5	0.007	0.319	0.042	75.396
		7	0.005	0.203	0.0015	49.550

0.026 for TOM, SOV, and spontan, respectively. Accordingly, TOM will be estimated by bell-shaped MF, as well as SOV and spontan should be predicted by a trapezoidal MF. And all of these MFs should apply 3 functions. Similarly, based on the Table 4.5, using non-FMCG dataset, the minimum test errors of TOM, SOV, and spontan are 0.037, 0.038 and 0.021, respectively. All the outputs should be predicted by trapezoidal MFs with 3 functions, for TOM, SOV, and spontan, respectively.

Table 4.4 : Training and test errors using FMCG data.

Output Type			Constant		Linear	
	MF Type	Number of MFs	Train Error	Test Error	Train Error	Test Error
TOM	triMF	3	0.022	0.064	0.016	2.451
		5	0.016	0.088	0.01	3.116
		7	0.009	1.063	0.000	8.033
	trapMF	3	0.024	0.049	0.017	0.086
		5	0.017	0.073	0.009	0.381
		7	0.012	2.559	0.000	3.217
	gbellMF	3	0.02	**0.048**	0.010	3.325
		5	0.011	0.101	0.155	444.877
		7	0.005	0.801	0.009	12.874
	gaussMF	3	0.02	0.053	0.011	11.652
		5	0.01	0.695	0.71	1858.194
		7	0.006	0.342	0.002	32.493
SOV	triMF	3	0.019	0.0409	0.017	5.921
		5	0.011	0.322	0.002	7.18
		7	0.004	0.474	0.000	9.035
	trapMF	3	0.03	**0.0400**	0.010	0.1000
		5	0.019	0.102	0.003	0.157
		7	0.016	0.086	0.000	10.031
	gbellMF	3	0.016	0.165	0.007	3.885
		5	0.009	1.166	0.093	462.852
		7	0.004	0.177	0.002	38.944
	gaussMF	3	0.018	0.277	0.009	17.336
		5	0.008	1.320	0.061	260.809
		7	0.002	0.227	0.000	15.695
Spontan	triMF	3	0.018	0.038	0.017	3.948
		5	0.015	0.212	0.007	23.690
		7	0.009	0.300	0.001	27.465
	trapMF	3	0.018	**0.026**	0.015	0.054
		5	0.017	0.038	0.007	0.234
		7	0.014	2.525	0.000	2.180
	gbellMF	3	0.015	0.047	0.012	1.432
		5	0.008	0.681	0.475	537.839
		7	0.006	0.459	0.003	14.329
	gaussMF	3	0.016	0.089	0.011	5.198
		5	0.010	0.925	0.109	422.508
		7	0.002	0.481	0.000	5.733

Table 4.6 summarizes the results of Tables 4.3, 4.4, and 4.5, and represents the appropriate type of fuzzy MFs and the number of them for each output.

As written in Table 4.6, in order to estimate TOM by using all data, the triple bell-shaped MFs of input variables factor1, factor2, and GRP are respectively depicted in Figures 4.1(a), 4.1(b), and 4.1(c). As mentioned before, there are three bell-shaped MFs in each fuzzy envelope, which stand for Low, Medium, and High linguistic

Table 4.5 : Training and test errors using non-FMCG data.

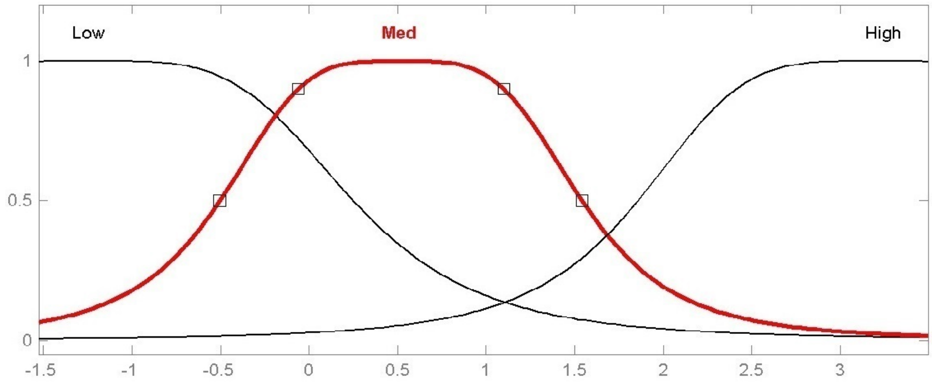
Output Type			Constant		Linear	
	MF Type	Number of MFs	Train Error	Test Error	Train Error	Test Error
TOM	triMF	3	0.026	0.048	0.019	11.516
		5	0.017	1.302	0.006	98.857
		7	0.006	0.571	0.001	29.329
	trapMF	3	0.025	**0.037**	0.020	82.324
		5	0.022	0.049	0.006	1.376
		7	0.015	0.467	0.000	0.781
	gbellMF	3	0.023	0.391	0.016	14.402
		5	0.017	2.106	0.188	525.787
		7	0.006	0.596	0.002	17.558
	gaussMF	3	0.024	1.419	0.015	72.188
		5	0.016	0.907	0.049	252.079
		7	0.006	0.521	0.001	19.876
SOV	triMF	3	0.006	0.164	0.004	2.485
		5	0.003	0.294	0.0004	7.693
		7	0.001	0.186	0.000	0.697
	trapMF	3	0.010	**0.038**	0.004	0.156
		5	0.006	0.356	0.0001	0.159
		7	0.002	0.070	0.000	0.528
	gbellMF	3	0.005	0.150	0.003	2.675
		5	0.002	0.171	0.023	21.257
		7	0.0005	0.153	0.0001	1.669
	gaussMF	3	0.0006	0.040	0.002	3.636
		5	0.001	0.205	0.004	16.426
		7	0.0007	0.173	0.0001	0.692
Spontan	triMF	3	0.014	0.11	0.011	3.006
		5	0.010	0.355	0.006	185.786
		7	0.005	0.426	0.0005	18.616
	trapMF	3	0.015	**0.021**	0.011	39.242
		5	0.011	0.106	0.005	0.299
		7	0.010	0.185	0.0008	0.675
	gbellMF	3	0.014	0.391	0.010	46.329
		5	0.007	0.371	0.189	273.569
		7	0.005	0.162	0.002	17.426
	gaussMF	3	0.014	0.044	0.009	19.416
		5	0.008	0.567	0.073	320.719
		7	0.004	0.227	0.002	16.496

Table 4.6 : Type and number of fuzzy MFs.

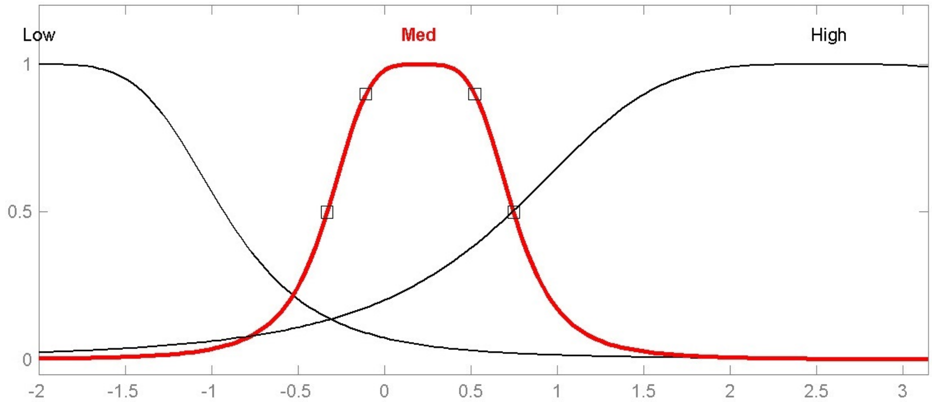
	TOM	**SOV**	**Spontan**
All Data	Bell, 3, Constant	Bell, 3, Constant	Trapezoidal, 3, Constant
FMCG	Bell, 3, Constant	Trapezoidal, 3, Constant	Trapezoidal, 3, Constant
Non-FMCG	Trapezoidal, 3, Constant	Trapezoidal, 3, Constant	Trapezoidal, 3, Constant

variables. For example, based on Figure 4.1(c), the left and right functions represent low and high GRP, as well as the middle function that graphs the medium GRP. Other

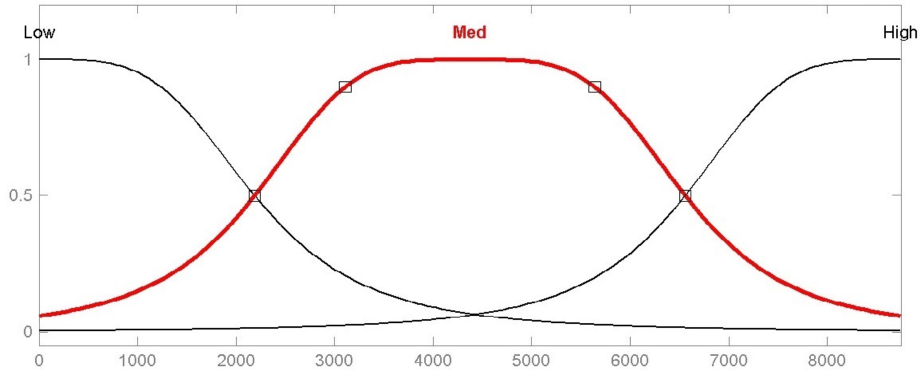
MFs of TOM, SOV, and spontan outputs, which are predicted by all data, FMCG data, and non-FMCG data, are attached to the Appendix A.2.



(a)



(b)



(c)

Figure 4.1 : MF of input variables for TOM estimation using all data: (a)Factor1. (b)Factor2. (c)GRP.

As mentioned before, ANFIS method estimates the outputs. The correlation between estimated and previously measured outputs are presented in Table 4.7.

There are 15 reputable Turkish companies which their brands are not mentioned here due to confidentiality of their advertising data. Here, these companies are named A to O. All data means data of all companies are pooled and analyzed together. FMCG or

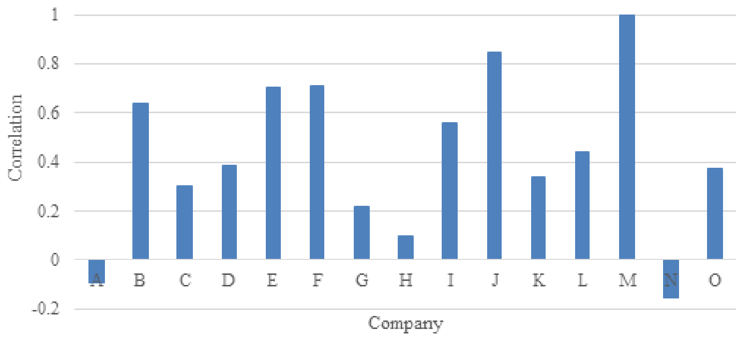
Table 4.7 : Correaltion of ANFIS estimations and measured outputs.

	TOM	SOV	Spontan
All Data	0.873	0.985	0.762
FMCG	0.983	0.975	0.848
Non-FMCG	0.795	0.990	0.820
A	0.272	0.849	0.564
B	0.545	0.963	0.552
C	0.582	0.969	0.589
D	-0.020	0.684	0.404
E	0.711	0.998	0.519
F	0.466	0.944	0.739
G	0.599	0.525	0.584
H	0.182	0.972	0.382
I	0.603	0.912	0.698
J	0.511	0.589	0.847
K	0.122	0.847	0.391
L	0.578	0.980	0.850
M	0.632	0.996	0.725
N	0.998	0.999	0.987
O	0.457	0.982	0.683

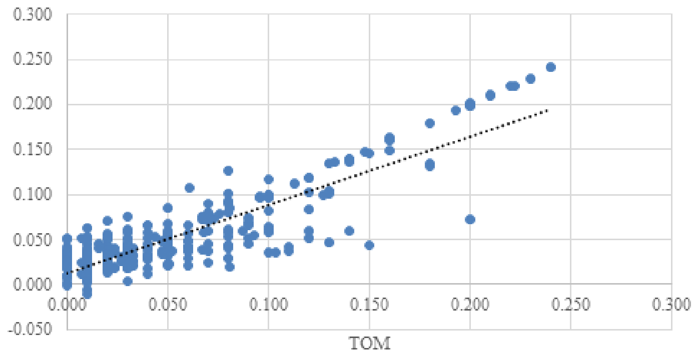
fast moving consumer goods refer to the producers of fast moving consumer goods, and FMCG row are the estimations of pooled data of 7 FMCG companies. Similarly, non-FMCG indicates companies which their products or services are not fast moving consumer goods, and remained 8 companies are non-FMCG, and their estimations are presented. Other alphabetic rows also represent the correlation of the estimation and measured data of each company, separately.

Using the input data and each output, we have depicted the estimations of ANFIS and measured values of TOM, SOV, and spontan, as well as their correlations in Figures 4.2, 4.3, and 4.4, respectively. In these figures, (a) shows the correlation values of companies and (b) depicts the scatter plots of predictions. Based on correlations and visible linearity scatter plots, the estimation of SOV is marvellous, and estimations of TOM and spontan are very good. In Table 4.7, the correlation values of TOM, SOV, and spontan using all data are 0.873, 0.985, and 0.762, respectively. These values also represent the thta the estimation of SOV is superior to TOM and spontan.

In order to validate the prediction of ANFIS, dataset splitted to 70 percent of data as training data and 30 percent as testing data. Using these trainng and testing data, RMSE of test data for TOM, SOV, and spontan are shown in Figures 4.5(a), 4.5(b), and

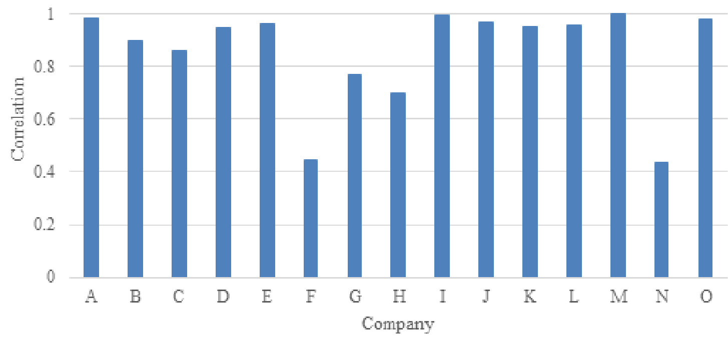


(a)

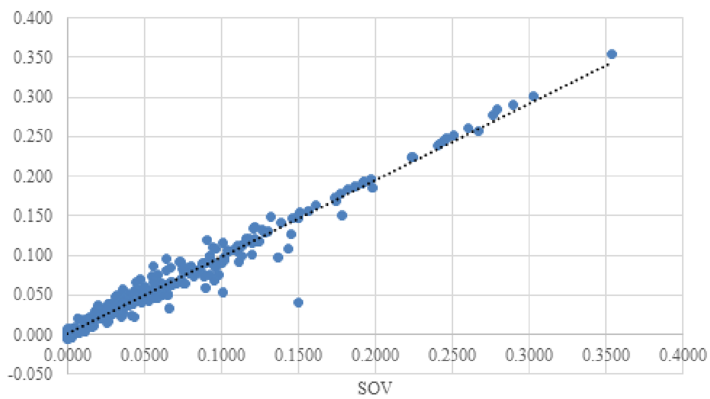


(b)

Figure 4.2 : TOM and estimated TOM using all data: (a)Correlations. (b)Scatter plot.



(a)



(b)

Figure 4.3 : SOV and estimated SOV using all data: (a)Correlations. (b)Scatter plot.

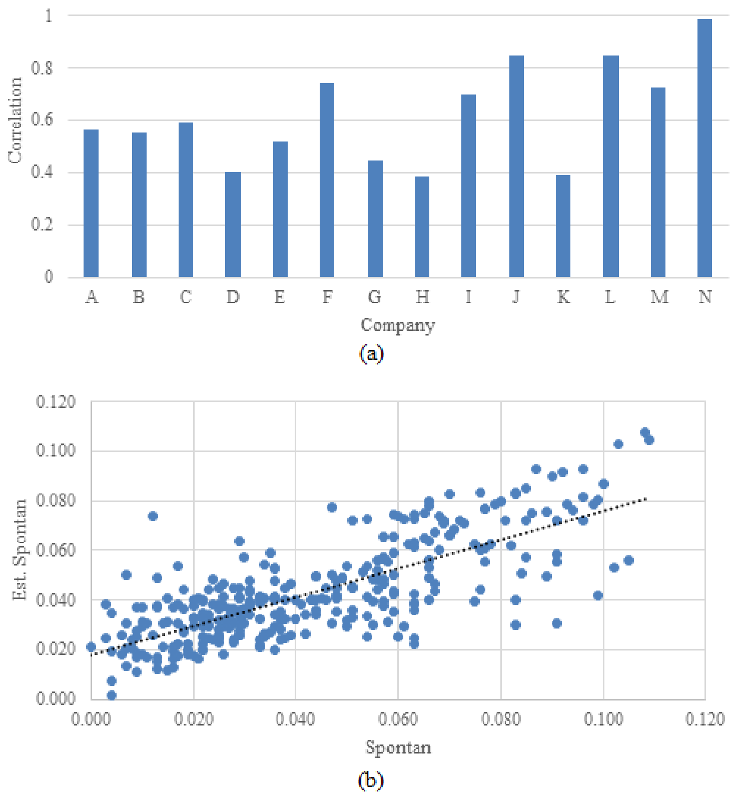
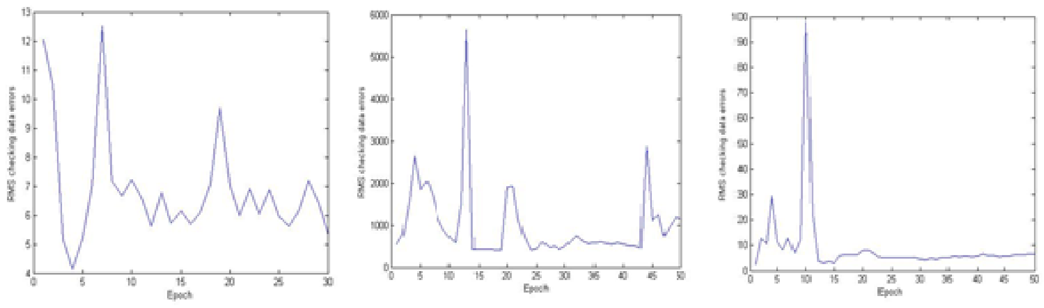


Figure 4.4 : Spontan and estimated Spontan using all data: (a)Correlations. (b)Scatter plot.

4.5(c), respectively. As shown below, using appropriate numbers of epochs, RMSE is decreasing in all of them.



(a) (b) (c)

Figure 4.5 : RMSE of test data using all data: (a)TOM. (b)SOV. (c)Spontan.

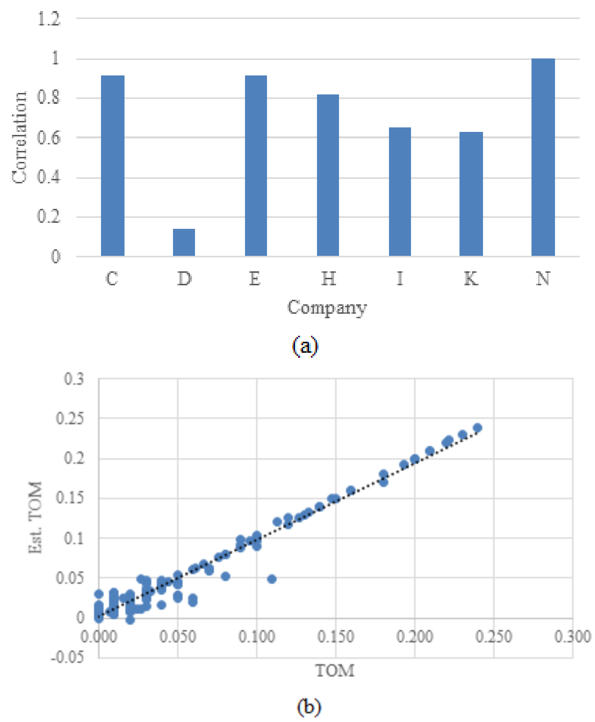


Figure 4.6 : TOM and estimated TOM using FMCG data: (a)Correlations. (b)Scatter.

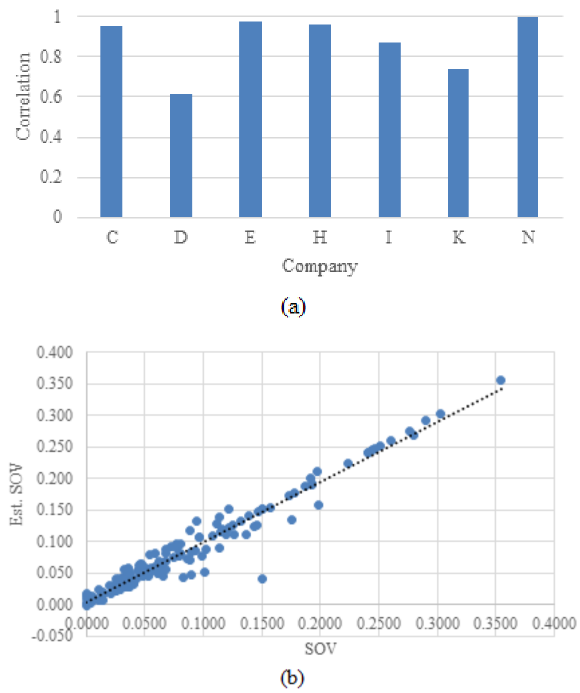


Figure 4.7 : SOV and estimated SOV using FMCG data: (a)Correlations. (b)Scatter plot.

Using FMCG data, the estimation of ANFIS and measured values of TOM, SOV, and sponton, as well as their correlations are displaied in Figures 4.6, 4.7, and 4.8, respectively. The correlations between measured and estimated TOM, SOV, and spontan are 0.983, 0.975, and 0.848, respectively. Based on the linearity of scatter plots and R values of graphs below, the estimation of TOM and SOV are marvellous, and estimations of spontan is good.

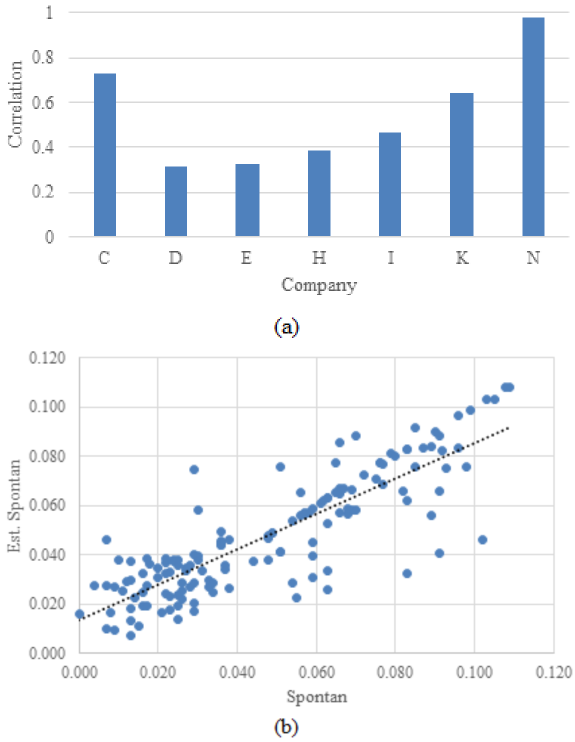


Figure 4.8 : Spontan and estimated Spontan using FMCG data: (a)Correlations. (b)Scatter plot.

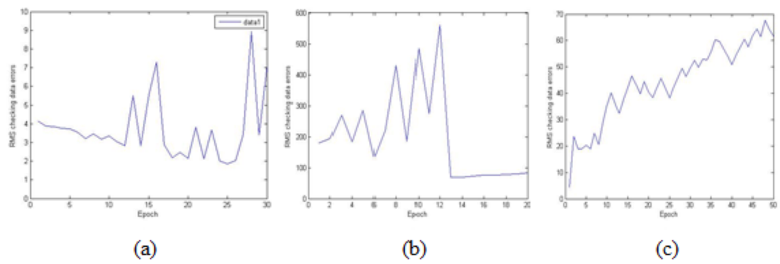
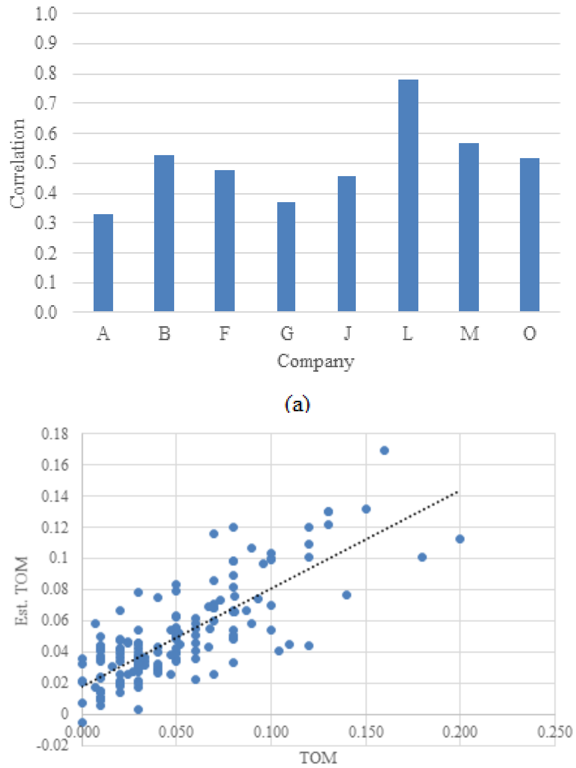


Figure 4.9 : RMSE of test data using FMCG data: (a)TOM. (b)SOV. (c)Spontan.

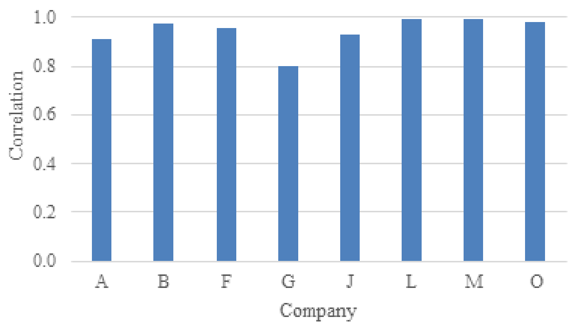
The RMSE graphs of testing data using FMCG dataset for TOM, SOV, and spontan are shown in Figure 4.9(a), 4.9(b), and 4.9(c). As training goes on, RMSE of TOM and SOV are decresing, but RMSE of spontan shows increasing.

The estimations of ANFIS and measured data of TOM, SOV, and spontan using non-FMCG dataset are presented in Figures 4.10, 4.11, and 4.12, respectively. As written in Table 4.7, the correlation of TOM, SOV, and spontan using non-FMCG are 0.795, 0.0.990, and 0.820, respectively. These values reveal that SOV and estimation of SOV are highly correlated. Figure 4.11 also shows that SOV possesses the most linearity, followed by TOM and spontan.

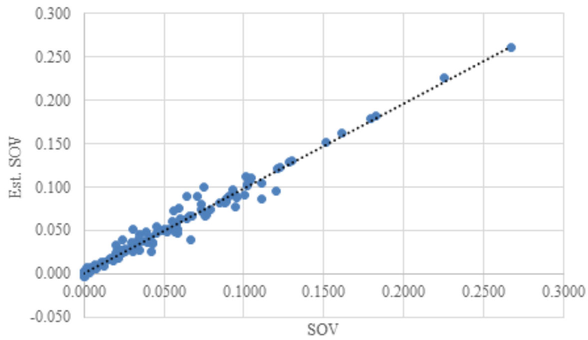


(b)

Figure 4.10 : TOM and estimated TOM using non-FMCG data: (a)Correlations. (b)Scatter plot.

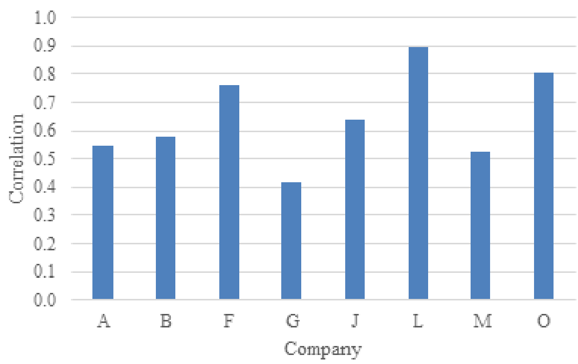


(a)

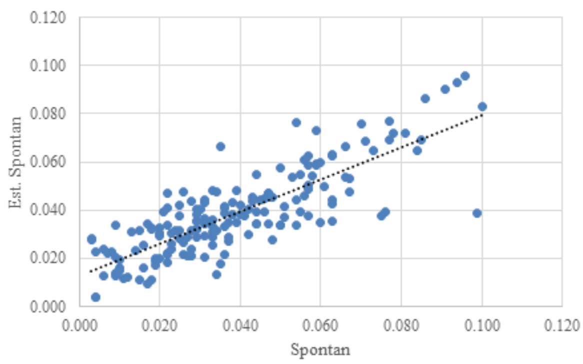


(b)

Figure 4.11 : SOV and estimated SOV using non-FMCG data: (a)Correlations. (b)Scatter plot.



(a)



(b)

Figure 4.12 : Spontan and estimated Spontan using non-FMCG data: (a)Correlations. (b)Scatter plot.

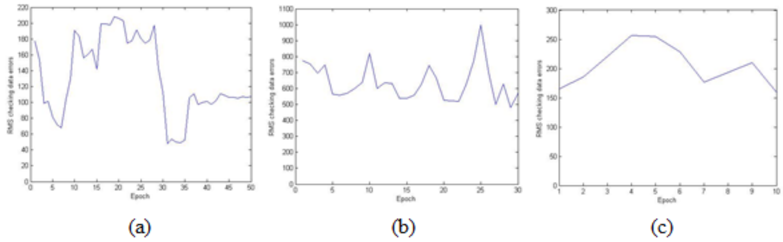


Figure 4.13 : RMSE of test data using non-FMCG data: (a)TOM. (b)SOV. (c)Spontan.

The estimations of ANFIS and measured output data, as well as correlations of company E, which is a FMCG company, are provided in Figures 4.14, 4.15, and 4.16 for TOM, SOV, and spontan, respectively. As shown in these figures and R^2 values written on the figures, the measurement and estimation of SOV are highly correlated, followed by TOM and spontan are not. Therefore, although the pooled data of all companies as well as the pooled data of FMCG companies are highly correlated with ANFIS estimations, the measured and estimated data of company E as a FMCG company are not highly correlated.

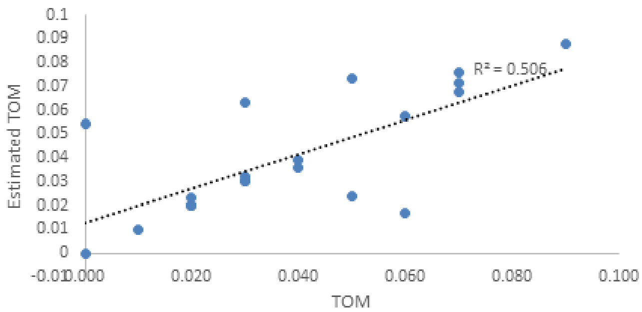


Figure 4.14 : TOM and estimated TOM of company E.

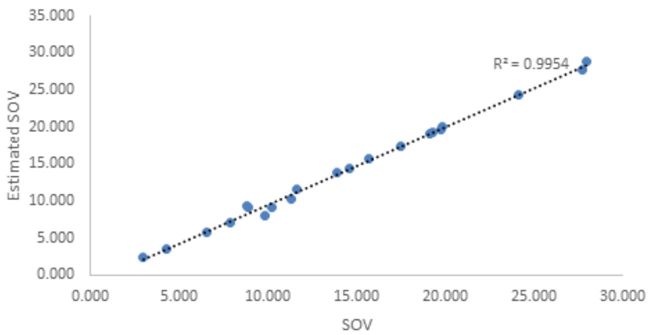


Figure 4.15 : SOV and estimated SOV of company E.

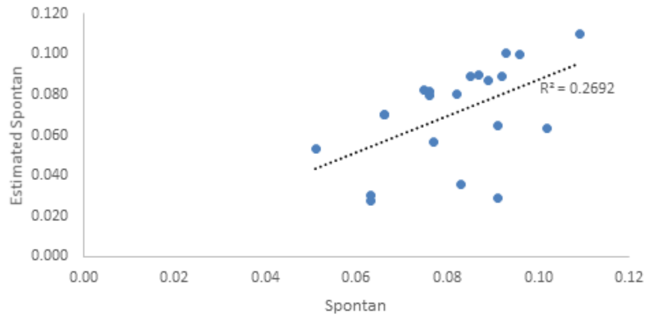


Figure 4.16 : Spontan and estimated spontan of company E.

Company B is a non-FMCG, and the TOM, SOV, and spontan graphs of ANFIS estimations and previously measured data of this company are depicted in Figures 4.17, 4.18, and 4.19, respectively. As represented below, the data of TOM and spontan are scattered and their R^2 values are 0.297 and 0.304, which are small. However, SOV data are linear and its R^2 is 0.927, which is close to 1.

Similar graphs of other FMCG and non-FMCG companies are added to the Appendix A.1.

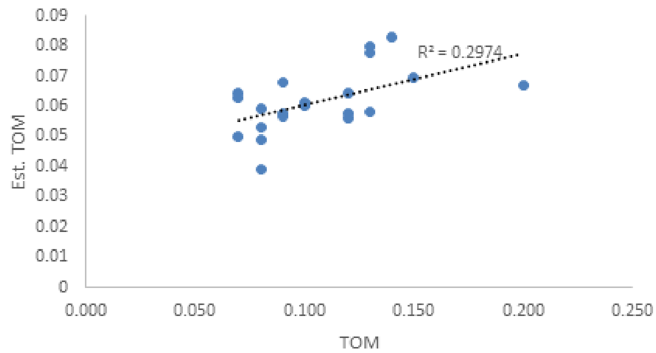


Figure 4.17 : TOM and estimated TOM of company B.

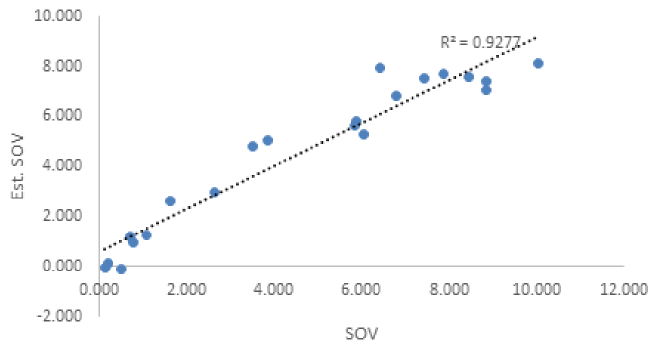


Figure 4.18 : SOV and estimated SOV of company B.

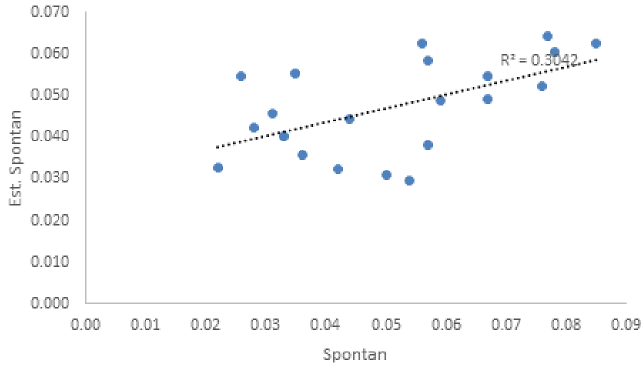


Figure 4.19 : Spontan and estimated spontan of company B.

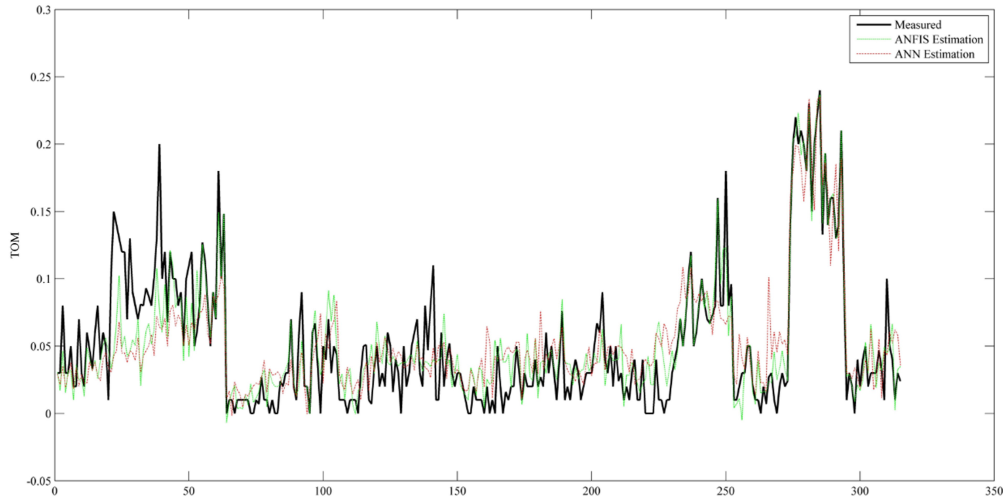
4.3 Comparing ANFIS and ANN

In order to investiagate the estimation power of ANFIS, we applied neural network and compared the results of both methods. Similar to previous analyses, using all data, FMCG and non-FMCG data, Figures 4.20, 4.21, and 4.22 represent the trained values of ANFIS, ANN, and measured data by green dashed, red dot dashed, and bold black lines, respectively. To reach a fair comparison, we considered similar parameters for ANFIS and ANN, i.e. the epochs and the percentage of test data were the same in both methods. In addition, we inserted different numbers of neurons of hidden layer and found 10 as the best number with the least training and test error.

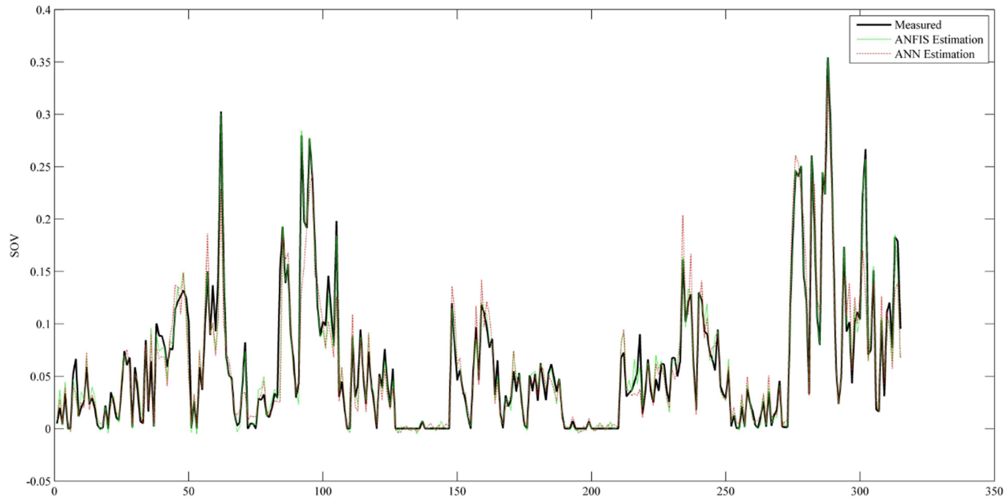
During the prediction process to obtain Figures 4.20, 4.21, and 4.22, we computed the correlation of ANFIS and ANN with measured data, which are gathered in Table 4.8. As you see, the correlations of ANFIS are greater than the correlations of ANN in all cases. This shows the superiority of ANFIS over ANN in predicting given data.

Table 4.8 : The correaltion of ANFIS and ANN estimations using all data, FMCG, and non-FMCG.

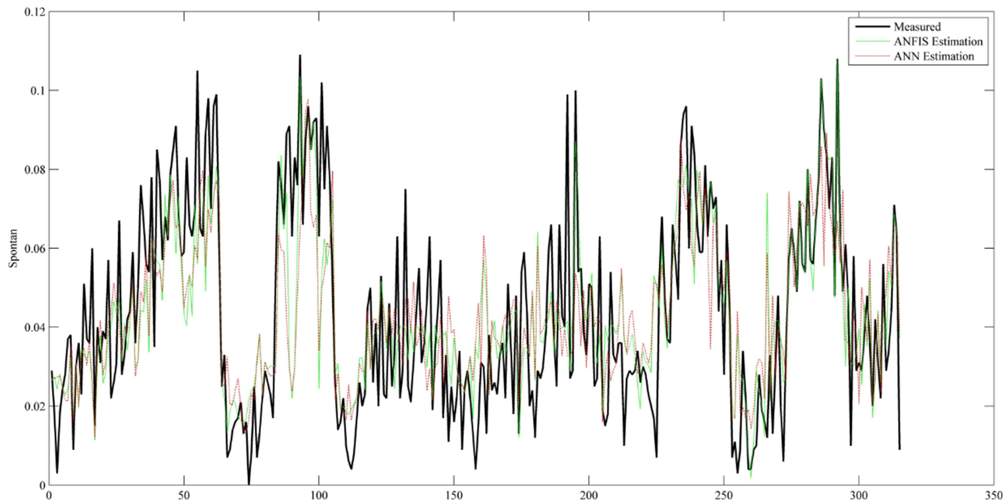
		ANFIS Correlation	**ANN Correlation**
All Data	TOM	0.879	0.791
	SOV	0.984	0.943
	Spontan	0.762	0.693
FMCG	TOM	0.986	0.905
	SOV	0.974	0.946
	Spontan	0.834	0.751
Non-FMCG	TOM	0.795	0.577
	SOV	0.990	0.956
	Spontan	0.820	0.520



(a)

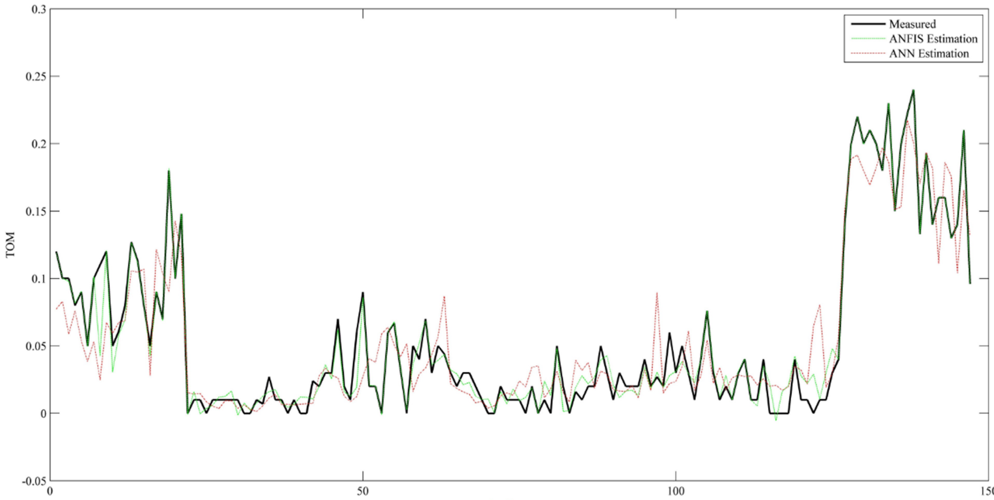


(b)

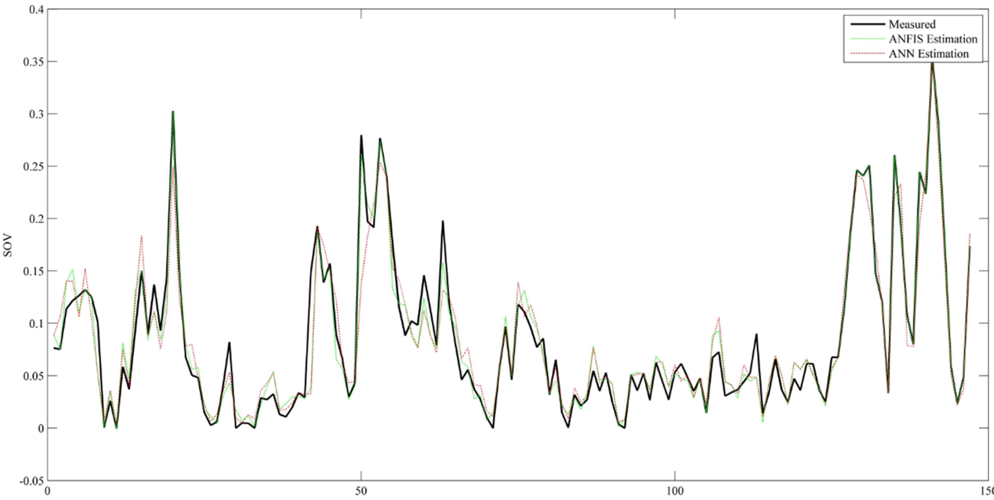


(c)

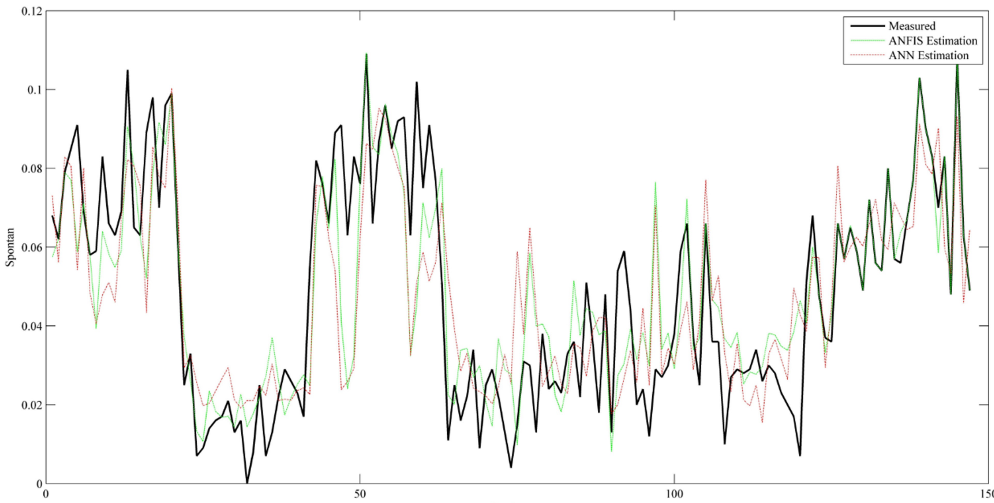
Figure 4.20 : Measured and predicted data using all data: (a)TOM. (b)SOV. (c)Spontan.



(a)

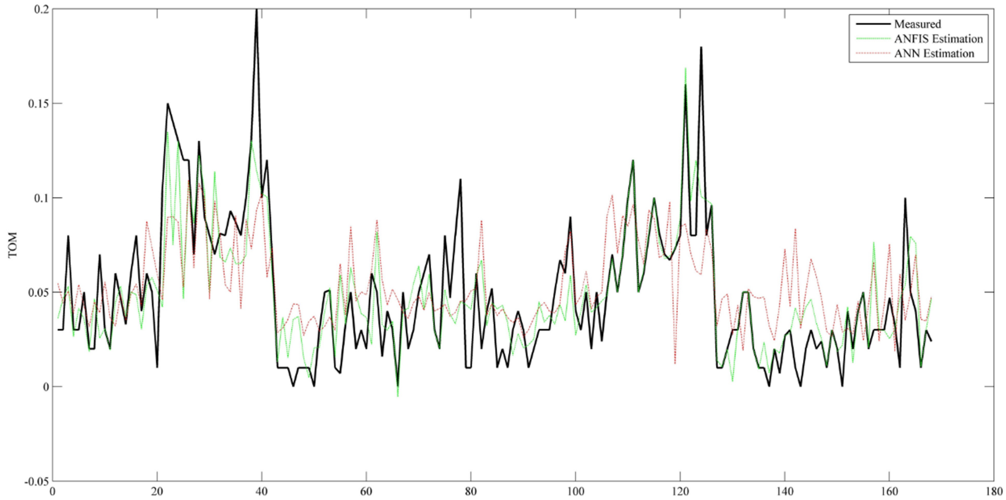


(b)

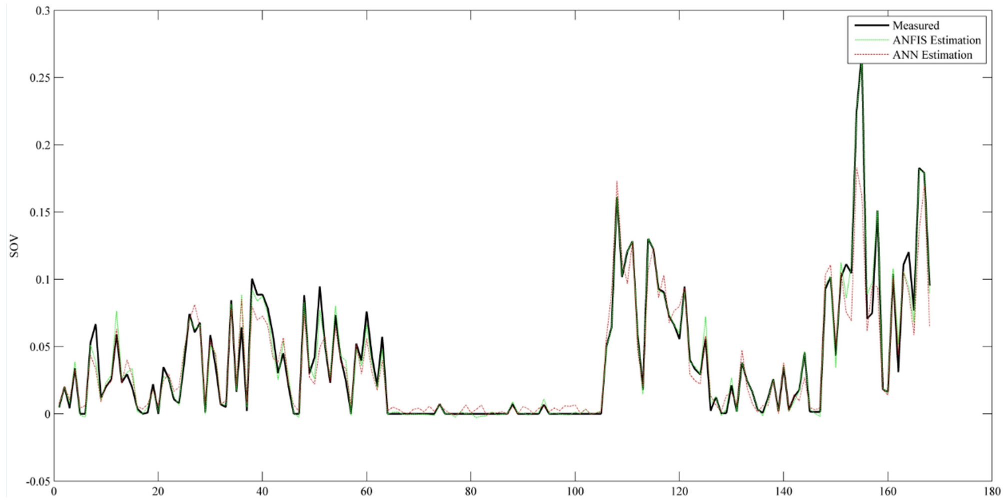


(c)

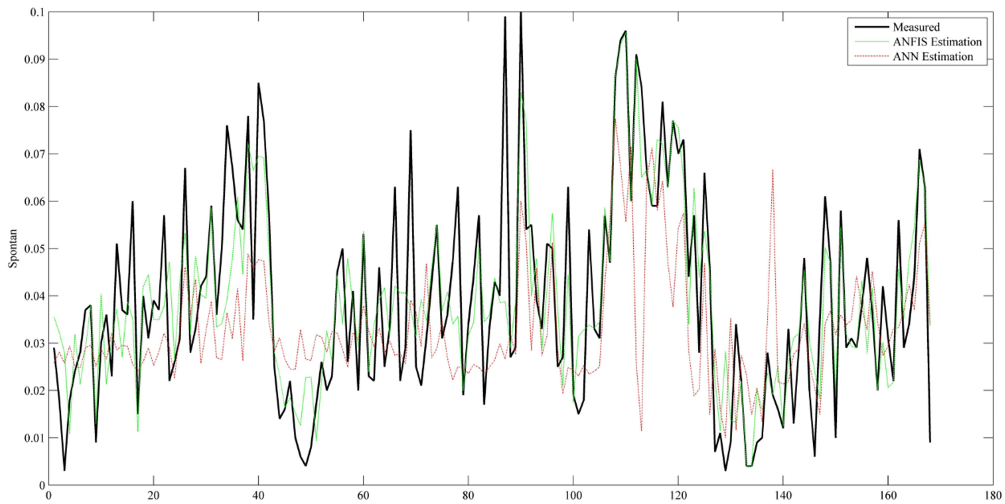
Figure 4.21 : Measured and predicted data using FMCG data: (a)TOM. (b)SOV. (c)Spontan.



(a)



(b)



(c)

Figure 4.22 : Measured and predicted data using non-FMCG data: (a)TOM. (b)SOV. (c)Spontan.

4.4 A Decision Support System to Predict Advertising Awareness

We have employed aforemantioned methods, ANFIS and ANN, to construct a DSS to predict advertising awareness. This DSS is programmed in MATLAB software, and can be also used to estimate any other types of dataset. It has three main components of each DSS, including data base, model base, and user interface. The model base exploits ANFIS and ANN to predict the output values using inputs, and compare the results. Figure A.21 shows the interface of the DSS with no uploaded dataset.

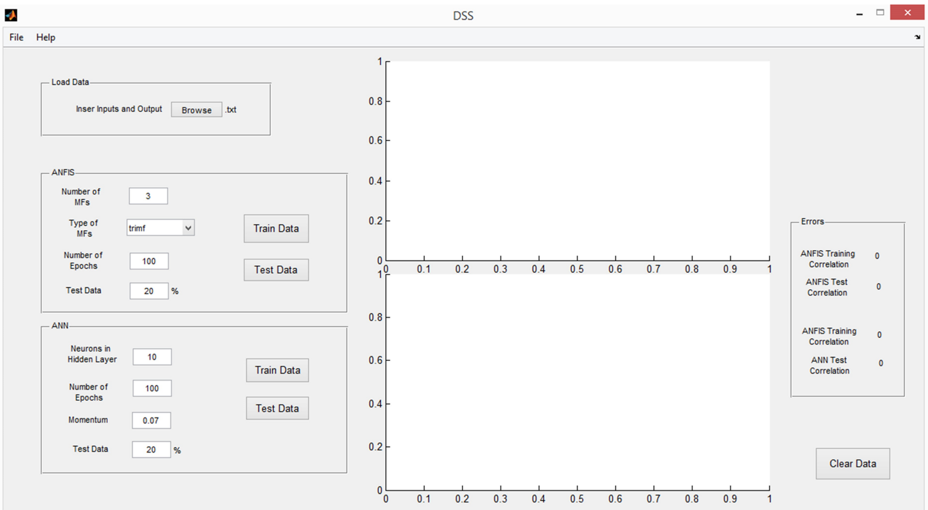


Figure 4.23 : The GUI of DSS.

As shown in Figure 4.24, all the inputs and TOM data are inserted in a single .txt file from the Load Data panel. In the ANFIS panel, we considered 2000 epochs, and 30 percent test data, which were chosen randomly. To predict this dataset, we also selected the optimal fuzzy sets for TOM using all data, i.e. bell-shaped MF with 3 function, as written in Table 4.3. The green dashed line and the bold black line show the ANFIS prediction and measured data, respectively. According to Figure 4.25, the test button of ANFIS panel is pressed and the error of ANFIS along with measured data are plotted in the bottom part of the interface. The correlations of training and test data are also calculated in the errors panel on the right side of interface.

In Figure 4.26, the prediction of ANN is added to the previsious estimation of ANFIS method. This provides the ability to compare the results. Finally, as shown in Figure 4.27, by pressing the test data button of ANN panel, the error of this method added to the bottom diagram. The correlation of ANN test is also appeared in the errors panel.

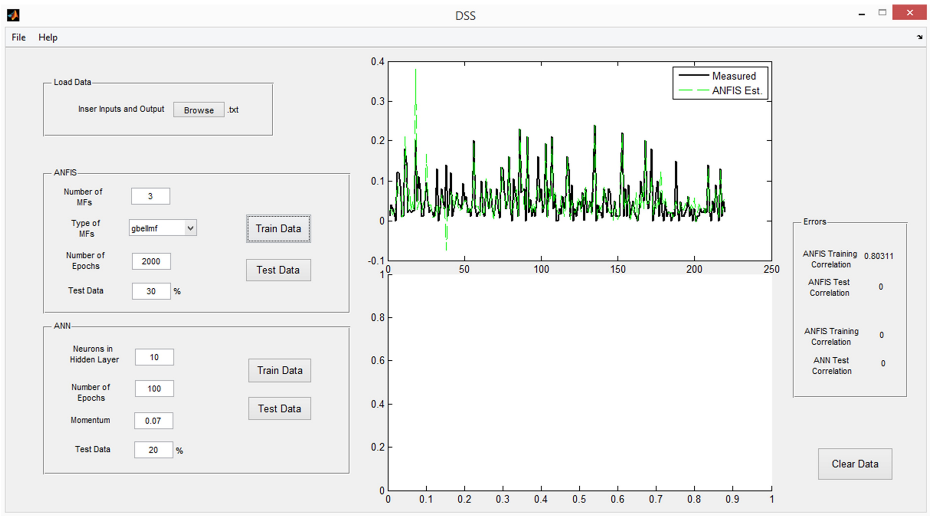


Figure 4.24 : The interface with ANFIS prediction.

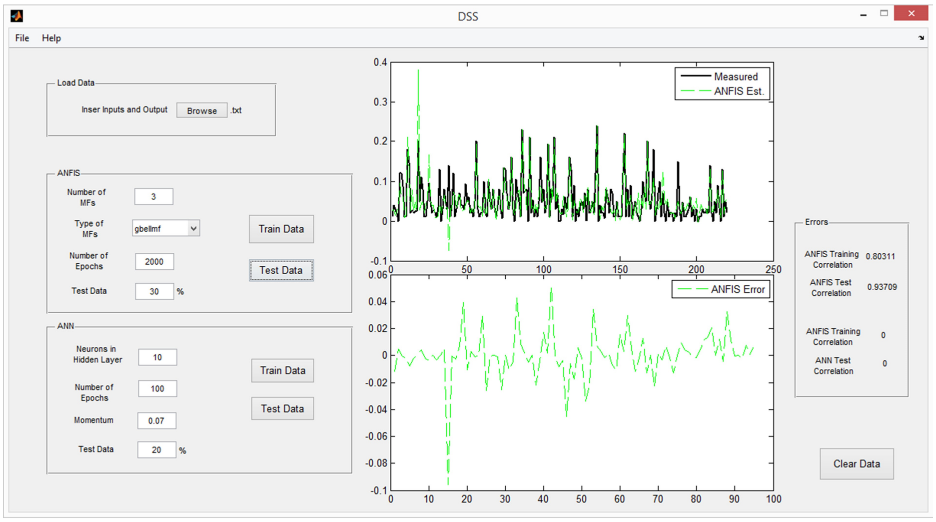


Figure 4.25 : The interface with ANFIS prediction and error.

Based on the correlation values of error panel, the outperformance of ANFIS is again obtain by developed DSS.

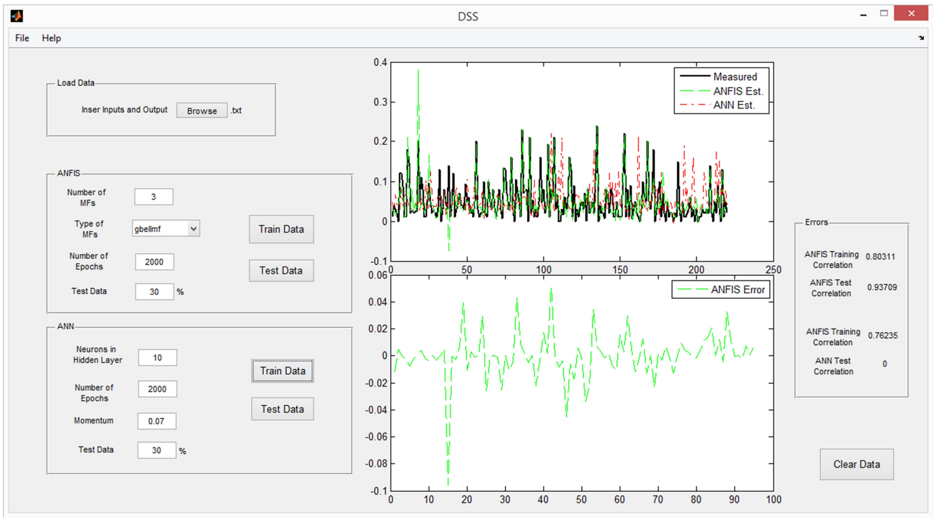


Figure 4.26 : The interface with ANFIS and ANN predictions and ANFIS error.

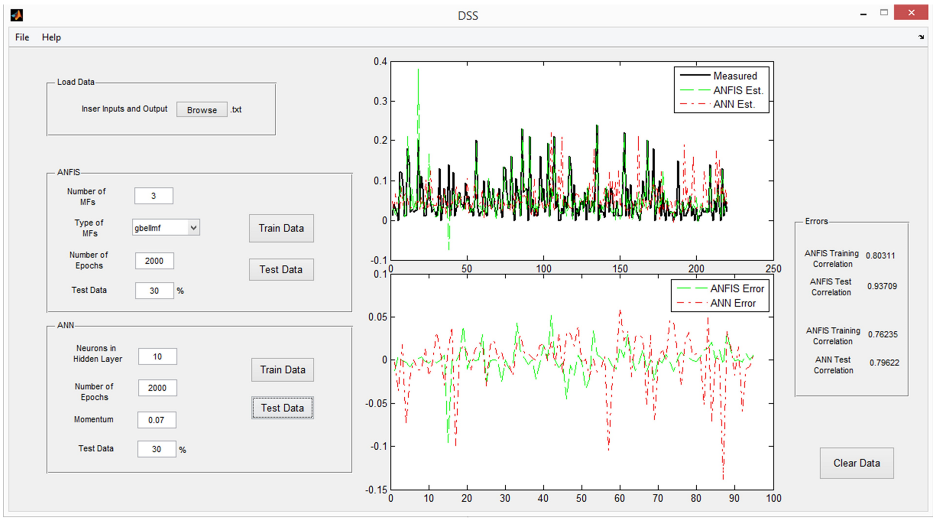


Figure 4.27 : The interface with ANFIS and ANN predictions and errors.

5. CONCLUSION AND FUTURE WORKS

The proposed method, adaptive neuro-fuzzy inference system (ANFIS), is applied to evaluate the effect of advertising on brand awareness. To evaluate the brand awareness of 15 prominent Turkish brands, a field study was conducted and people were asked to respond a questionnaire. There were 30 questions which formed the components of brand awareness, and three marketing metrics including TOM, SOV, and spontan. Since working with 30 variables is almost impossible, we used a dimension reduction method to reduce the number of input variables. Using PCA for 30 given variables, we obtained two principle components, plus GRP variable as the input variables. We considered these three inputs, as well as TOP, SOV, and spontan as the output variables of ANFIS. Each output variable was predicted separately and the prediction was also tested by using test data.

To test the validation of ANFIS predictions, 30 percent of data were randomly splitted as the test data and remained 70 percent were considered as training data. The RMSE graphs of most of the predicitons were decreasing, i.e. the prediction is conducted properly, and as training goes on, the errors were reducing in each epoch. The correlations of measurements and the predicitons of ANFIS method represent the power of estimations. According to these correlations, predicted data using SOV were perfectly correlated with the measured SOVs. The correlation of TOM and spontan were smaller than SOV's, but their predictions were correlated with the measured data.

In order to analyze homogeneous companies in appropriate categories, we classified the companies into two groups, FMCG and non-FMCG. The data of each group is consistent with each other, and the errors of their separate predictions are less than the pooled data. Using FMCG data, we estimated TOM, SOV, and spontan separately. The correlations between given data and ANFIS prediction revealed that TOM was the best predicited variable, followed by SOV which was estimated perfectly. And the prediction of spontan was also considered as very good. Accordingly, using non-FMCG data, the prediciton of SOV acheived the best correlation among output variables, followed by spontan and TOM, respectively.

If we observe TOM, SOV, and spontan with respect to the data type, i.e. all data, FMCG, and non-FMCG, we can see that TOM was properly predicted using FMCG data. SOV using using non-FMCG data was also reached the best predicition. And spontan was perfectly estimated by FMCG data. Consequently, it is better to classify the data set into FMCG and non-FMCG, then use ANFIS to predict brand awareness data.

Among all these analyses, we achieved the highest correlation prediction of SOV. The second correlation was the estimation of TOM using FMCG data. And, spontan had the lowest correlation among other variables using all types of data. In addition, considering the data of each company by itself, we considered very turbulent correlation between predicted outputs and given data. In some cases the prediction is highly correlated with given data, e.g. in E company's prediction of SOV. On the other hand, in other estimations we achived very low correlations.

Moreover, we considered ANN as the alternative prediction method and compared the results with ANFIS. Based on our findings and the correlation of predictions, ANFIS shows better performance than ANN in considering the same network parameters. Consequently, we can claim that ANFIS outperforms ANN in estimating our advertising awareness data.

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APPENDICES

APPENDIX A.1

Table A.1 : Advertising awareness questions (in Turkish).

No	Question
1	Güvenilirdir
2	Herkesin çalismak istedigi bir firmadir
3	yenilikçidir
4	yenilikçidir
5	Liderdir
6	Ekonomiye katkida bulunur
7	Itibarli ve saygindir
8	Kolaylikla erisebilecegim bir firmadir
9	Uluslarasi bir markadir
10	Genis bir ürün yelpazesi vardir
11	Günceldir, kendini yeniler
12	Muhafazakardir
13	Bana yakindir
14	Kadinlara yakin bir firmadir
15	Tüketicilerine deger verir
16	Olmasa eksikligini hissederim
17	Gurur duyarim
18	Içimizden biridir
19	Ürün/hizmetleri kalitelidir
20	ödenen paraya degerdir
21	Reklamlarini seyretmekten zevk aldigim bir firmadir
22	Eglenceli bir firmadir
23	Toplumsal projelere/ Sosyal sorumluluk projelerine önem verir
24	Çocuklari ve gençleri futbolu ve basketbolu sevmeye tesvik eder.
25	Türkiye'de sporun gelisimi için Kulüp ve spor organizasyonlarina yatirim yapar
26	Çocuklara yönelik sinema, tiyatro gibi kültürel aktiviteleri destekler
27	Müsterilerine/tüketicilerine her yerde çesitli mutluluklar sunar
28	Gençlere hitap eder
29	Çevreye duyarlidir
30	Sanata ve sanatin gelisimine katkida bulunur

APPENDIX A.2

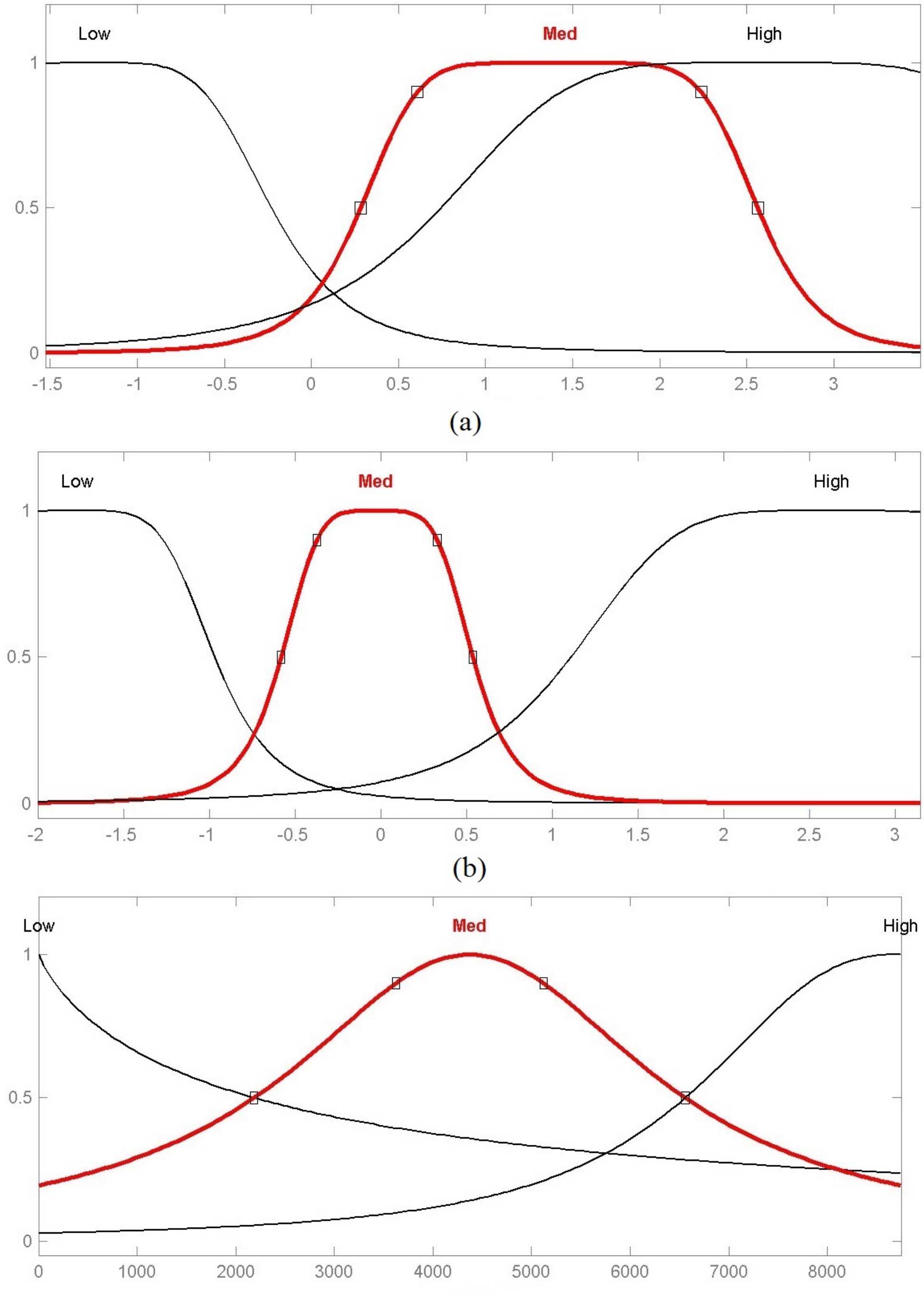
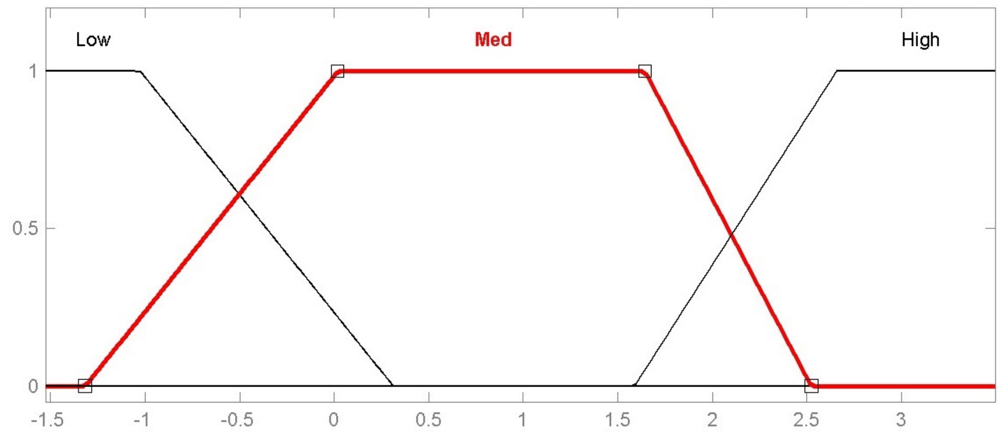


Figure A.1 : Membership functions of input variables for SOV estimation using all data: (a)Factor1. (b)Factor2. (c)GRP.



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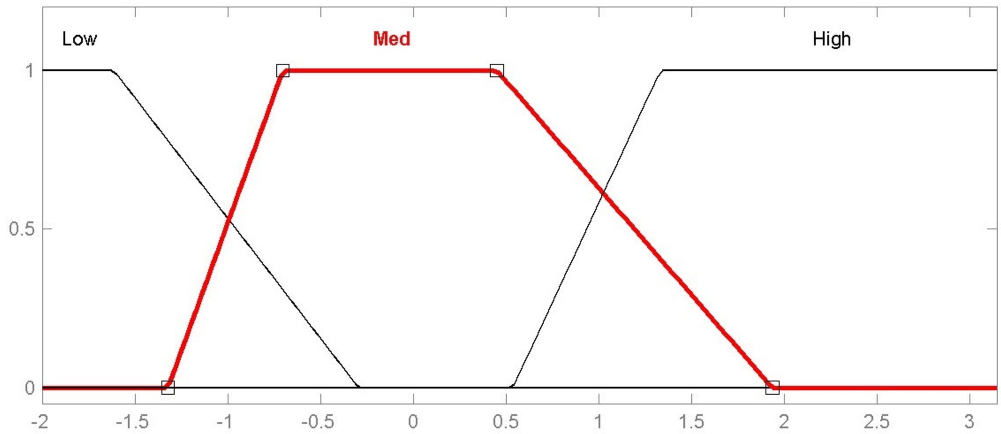

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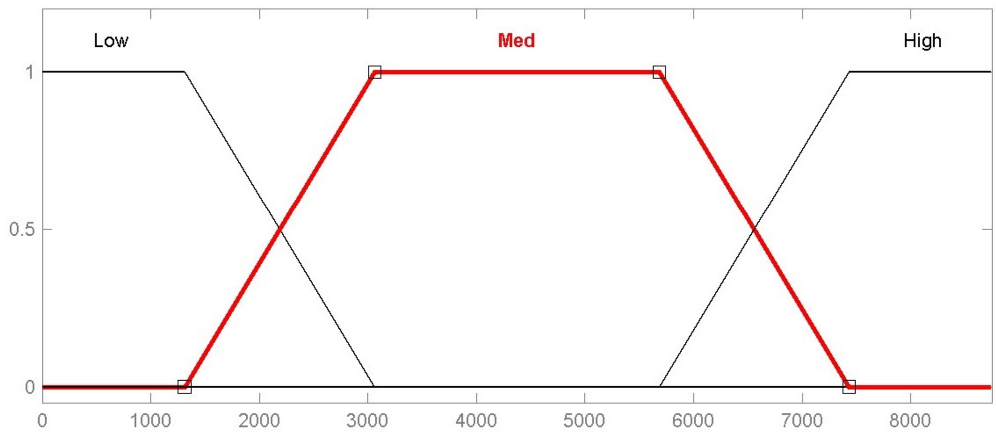
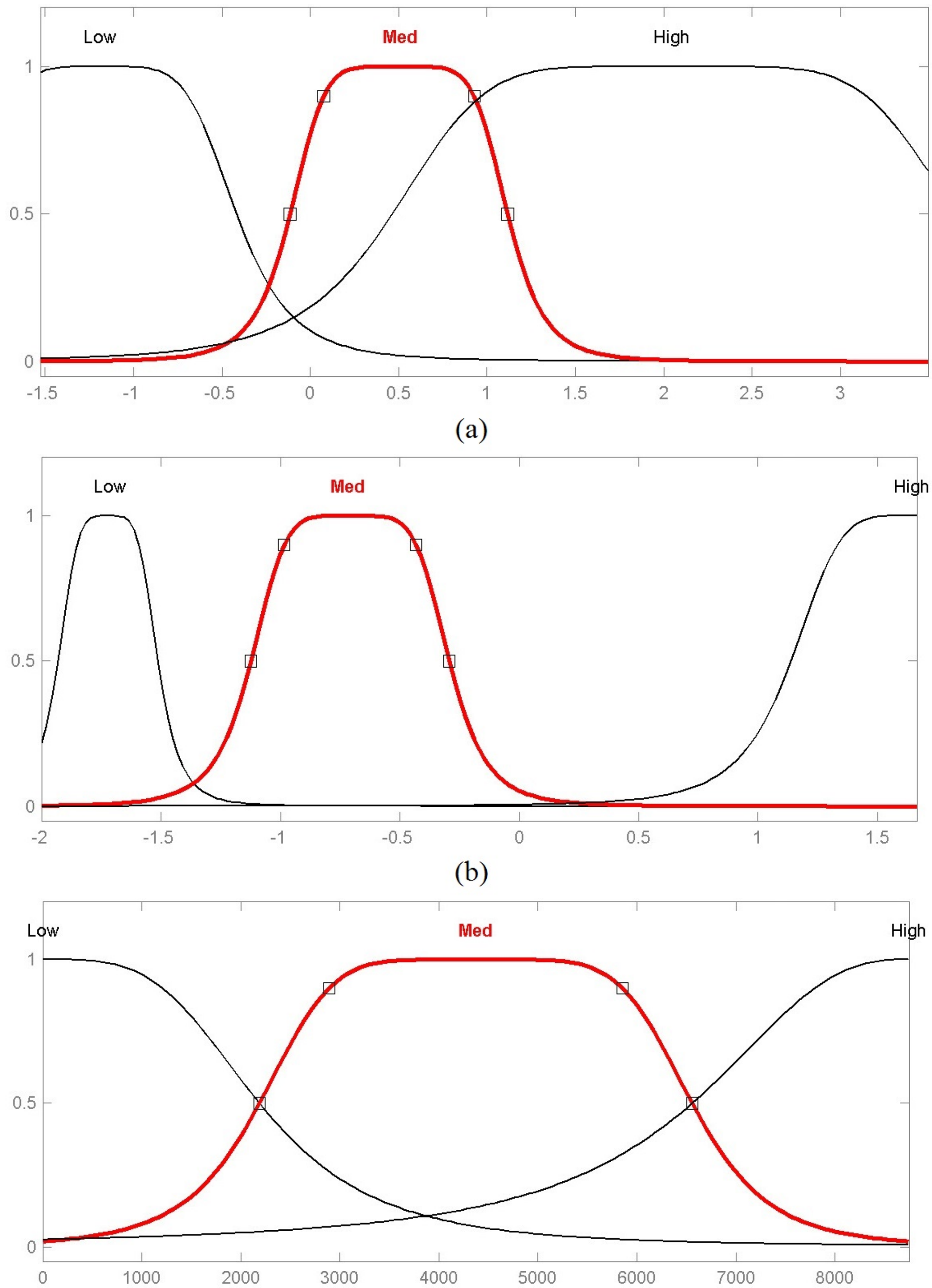


(c)

Figure A.2 : Membership functions of input variables for spontan estimation using all data: (a)Factor1. (b)Factor2. (c)GRP.

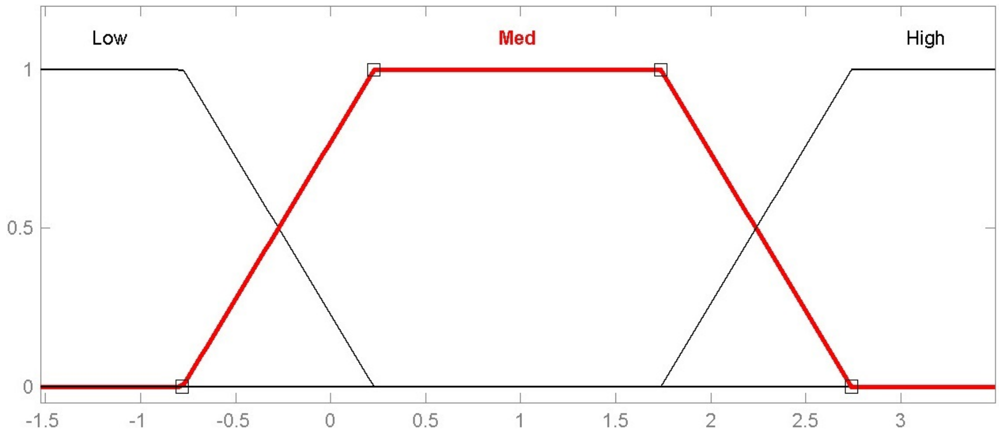


(a)

(b)

(c)

Figure A.3 : Membership functions of input variables for TOM estimation using FMCG data: (a)Factor1. (b)Factor2. (c)GRP.



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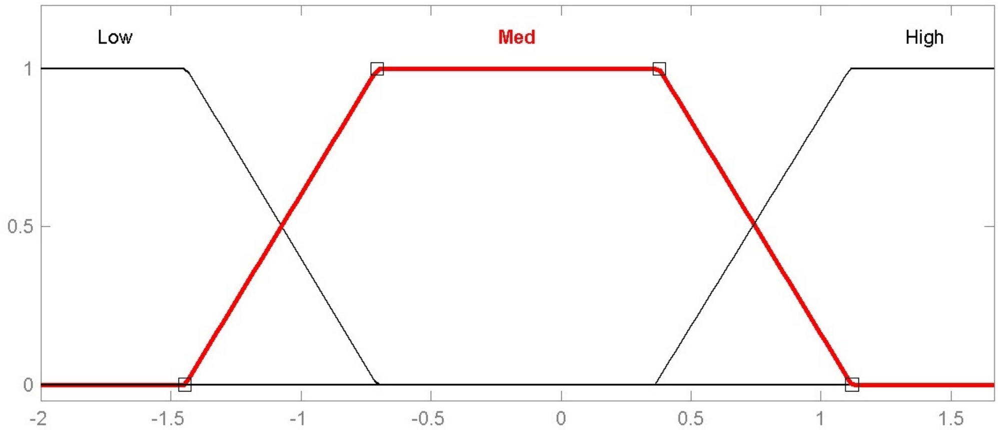

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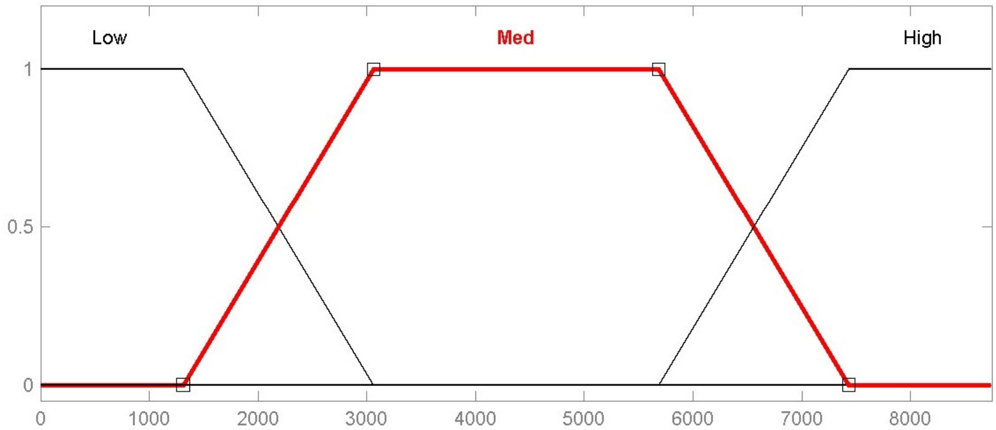


(c)

Figure A.4 : Membership functions of input variables for SOV estimation using FMCG data: (a)Factor1. (b)Factor2. (c)GRP.

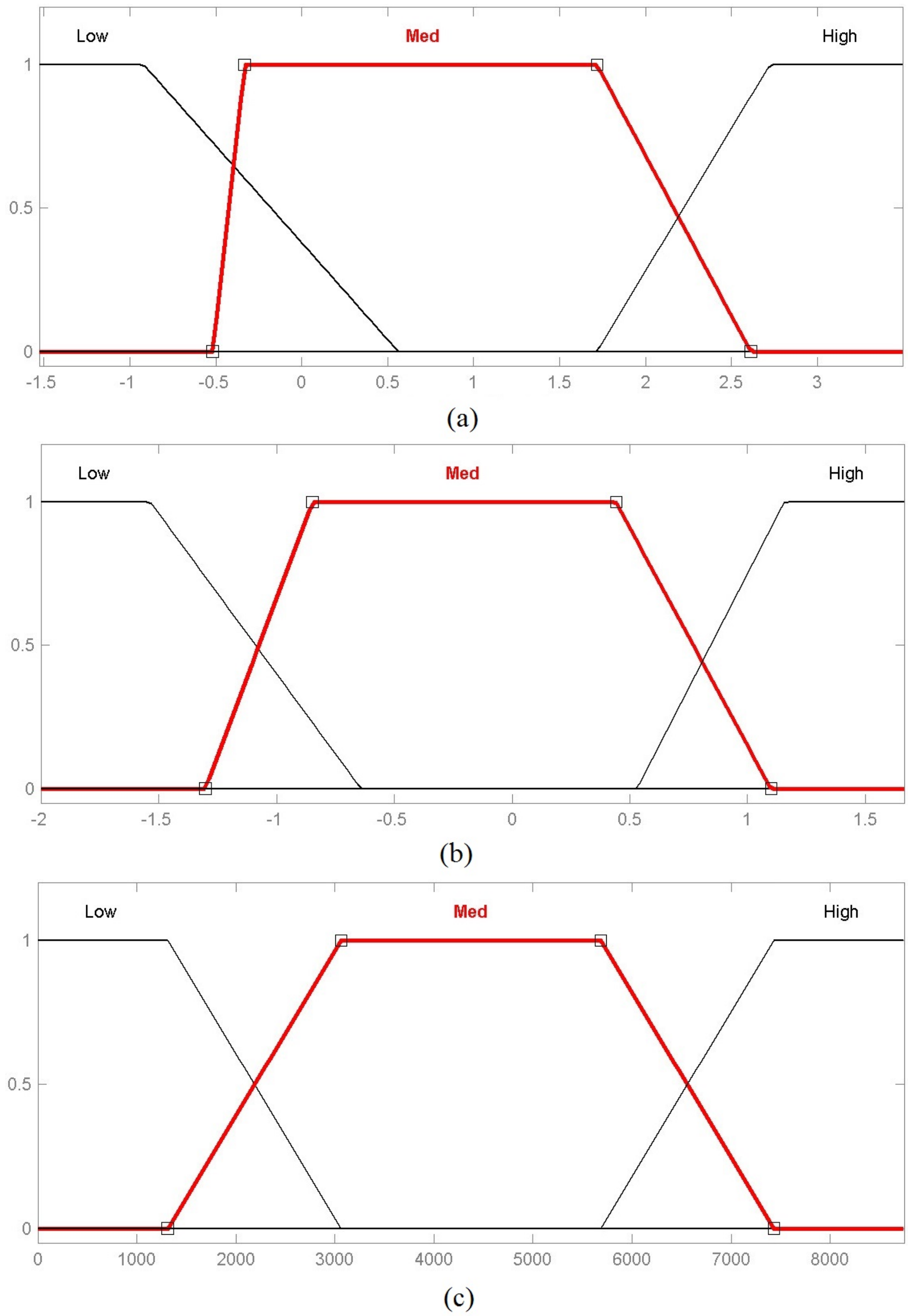
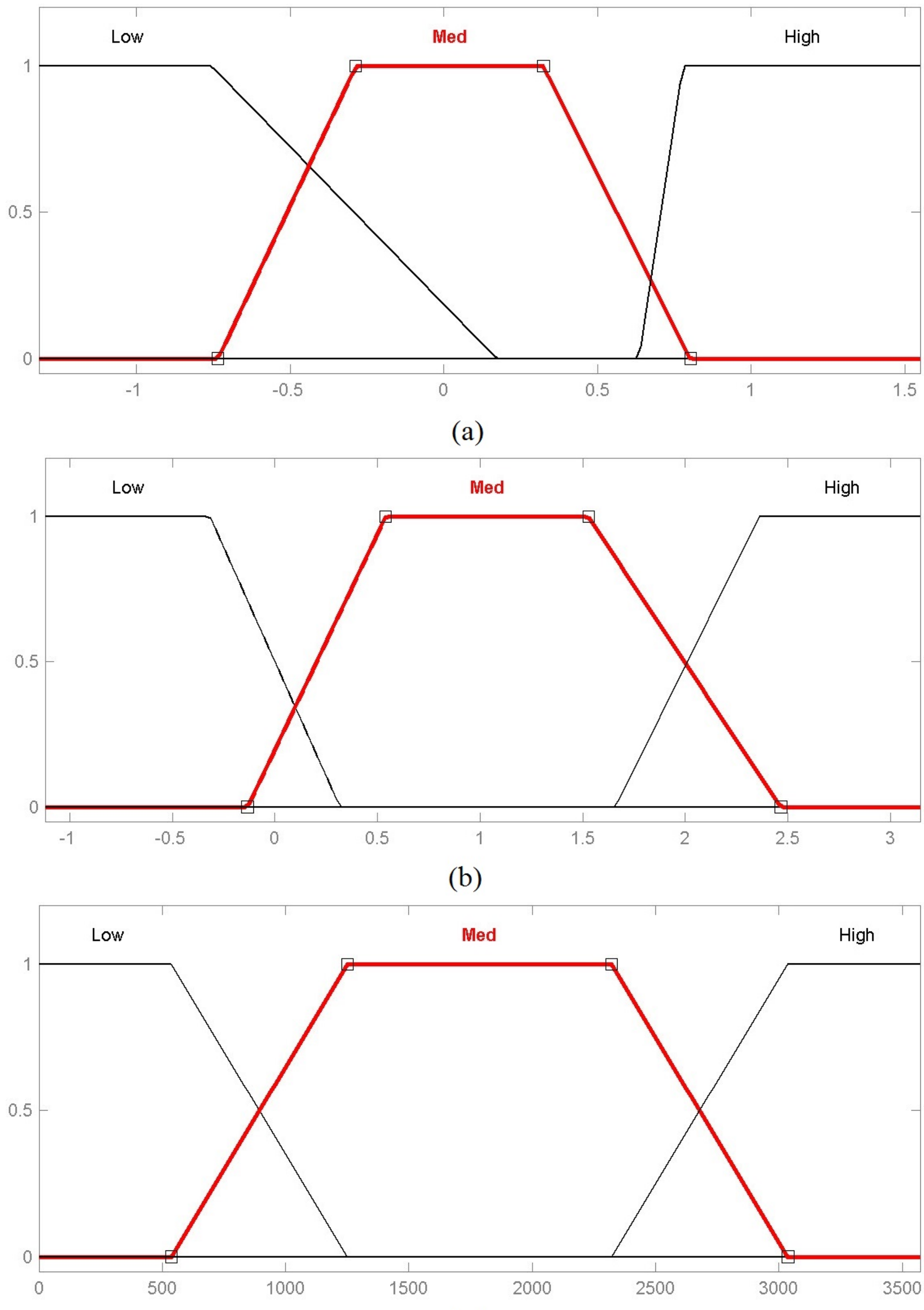


Figure A.5 : Membership functions of input variables for spontan estimation using FMCG data: (a)Factor1. (b)Factor2. (c)GRP.



(c)

Figure A.6 : Membership functions of input variables for TOM estimation using non-FMCG data: (a)Factor1. (b)Factor2. (c)GRP.

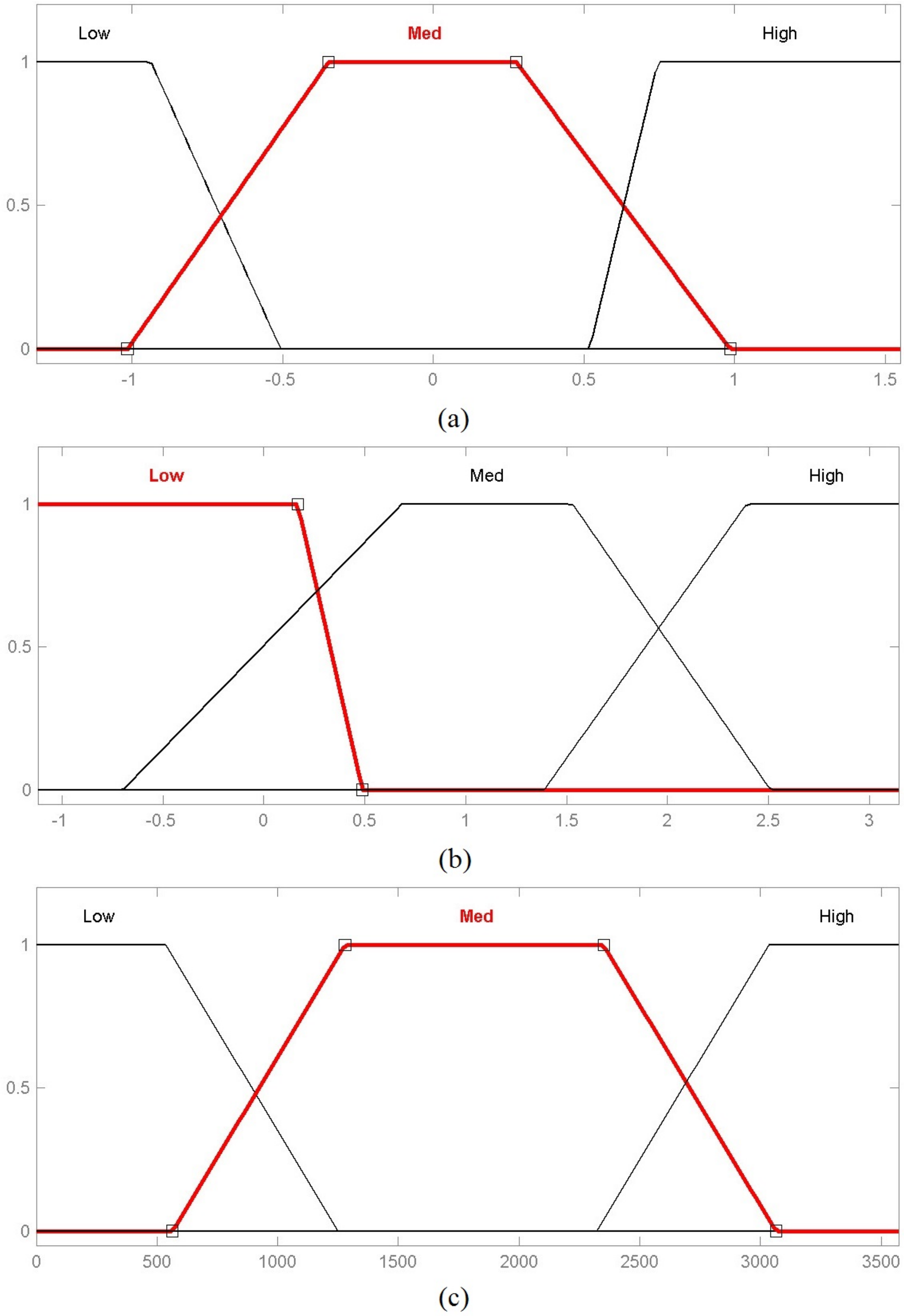
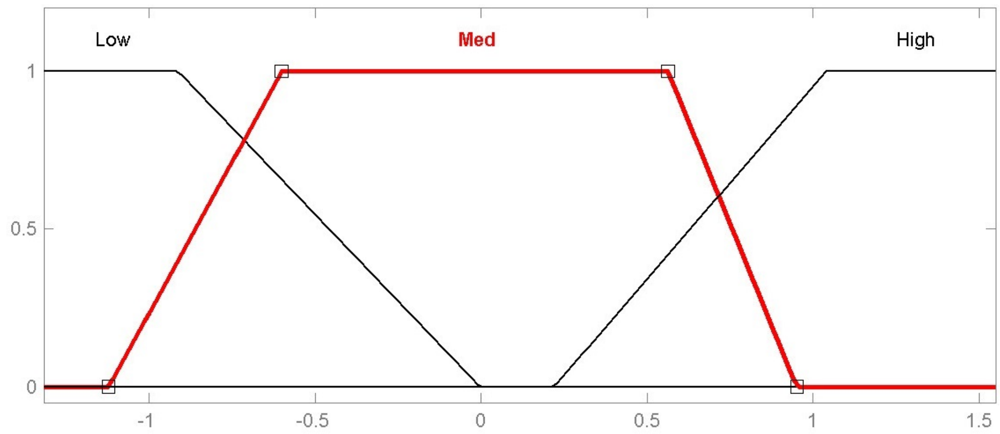


Figure A.7 : Membership functions of input variables for SOV estimation using non-FMCG data: (a)Factor1. (b)Factor2. (c)GRP.



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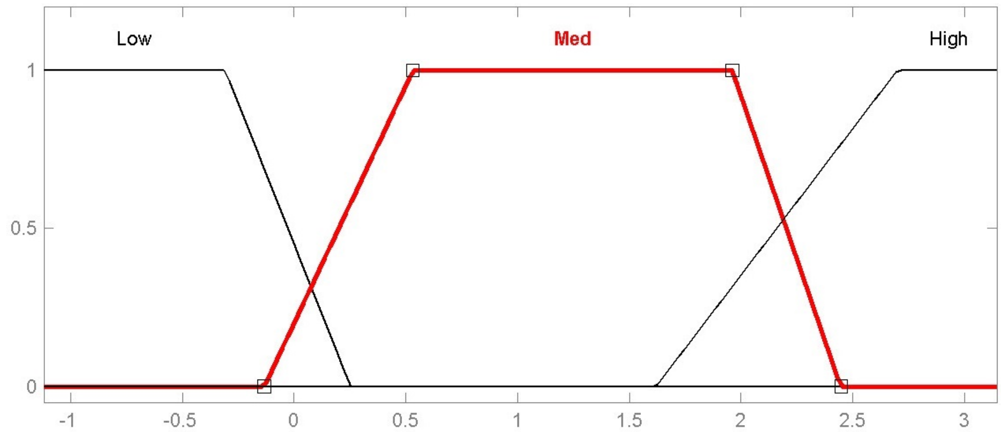

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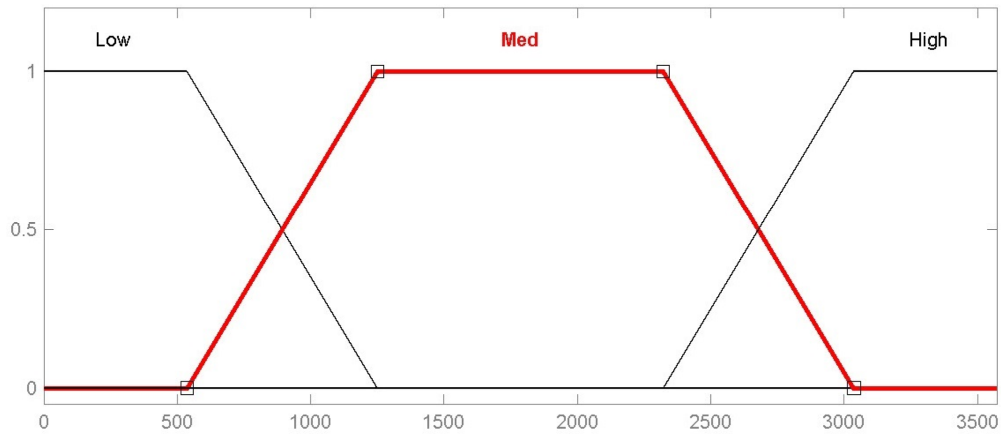
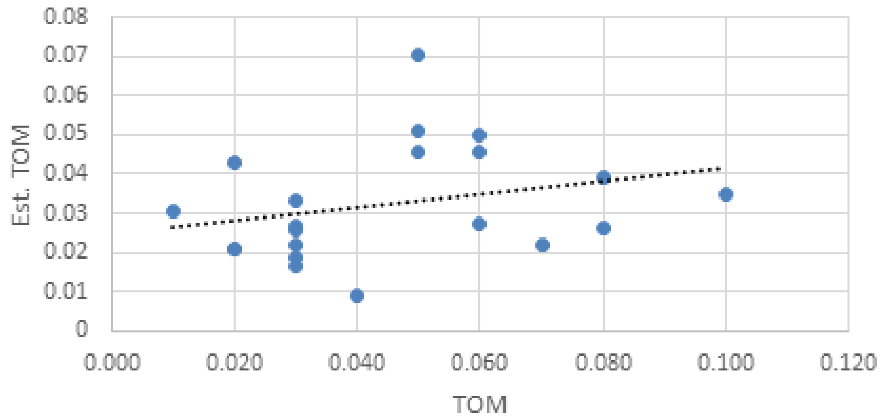


(c)

Figure A.8 : Membership functions of input variables for spontan estimation using non-FMCG data: (a)Factor1. (b)Factor2. (c)GRP.

APPENDIX A.3



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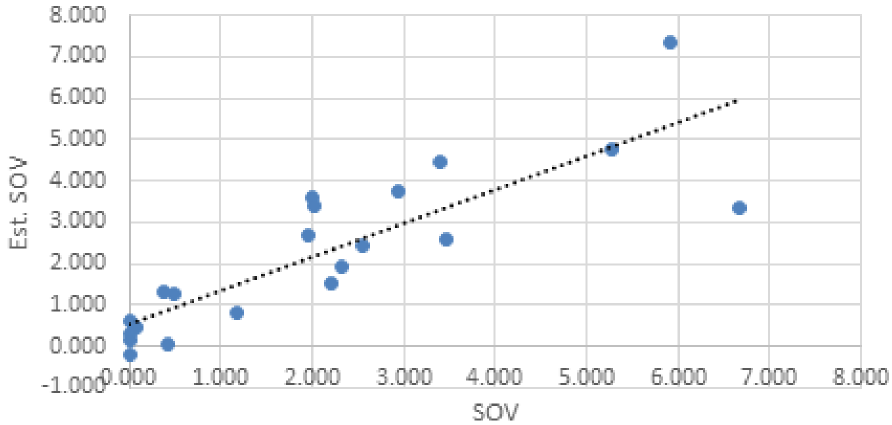

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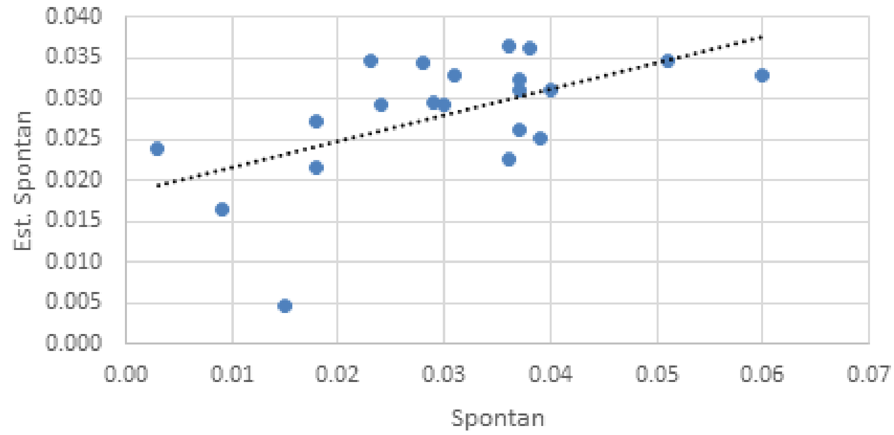
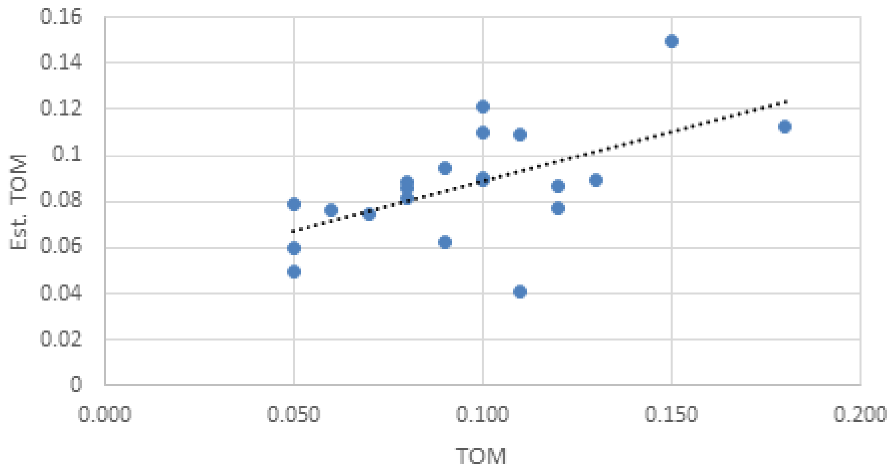


(c)

Figure A.9 : Scatter plot of estimated and measured data of company A: (a)TOM. (b)SOV. (c)Spontan.



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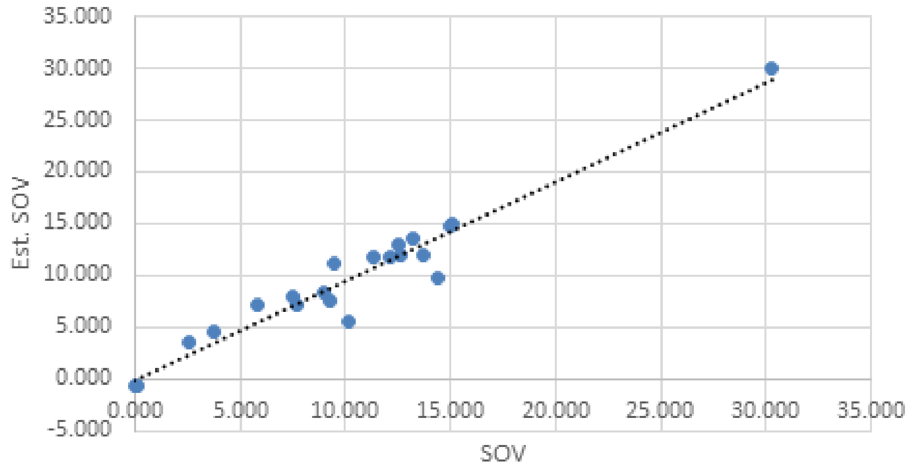

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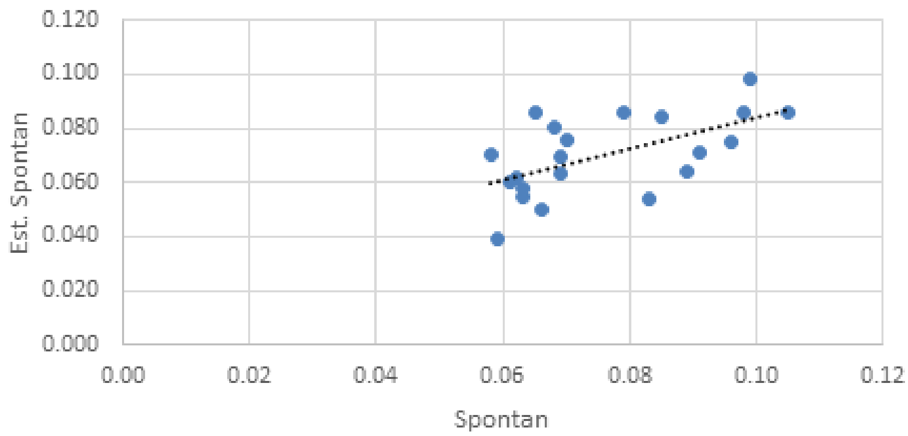

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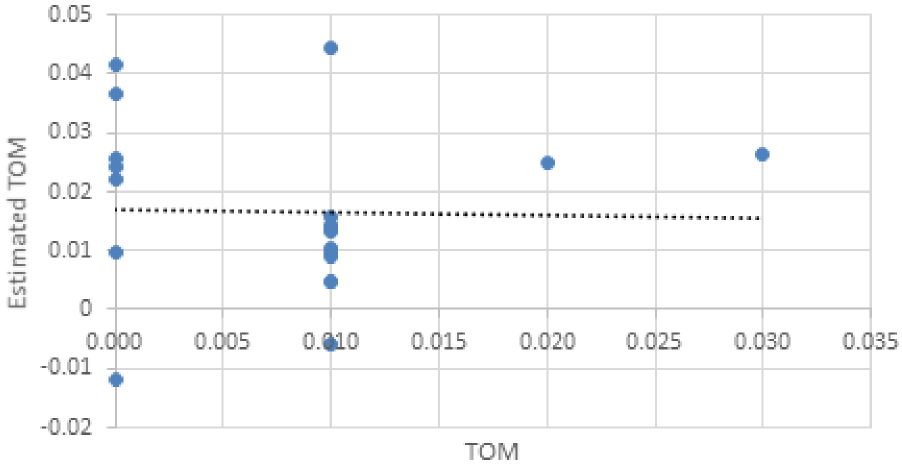
Figure A.10 : Scatter plot of estimated and measured data of company C: (a)TOM. (b)SOV. (c)Spontan.



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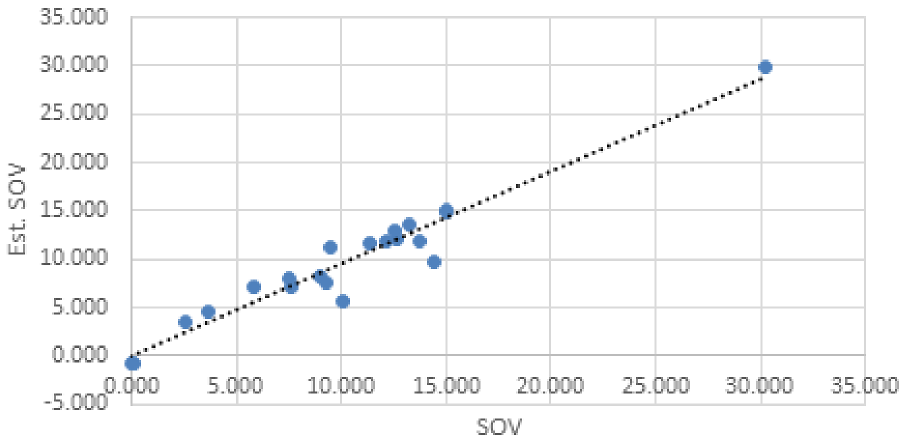

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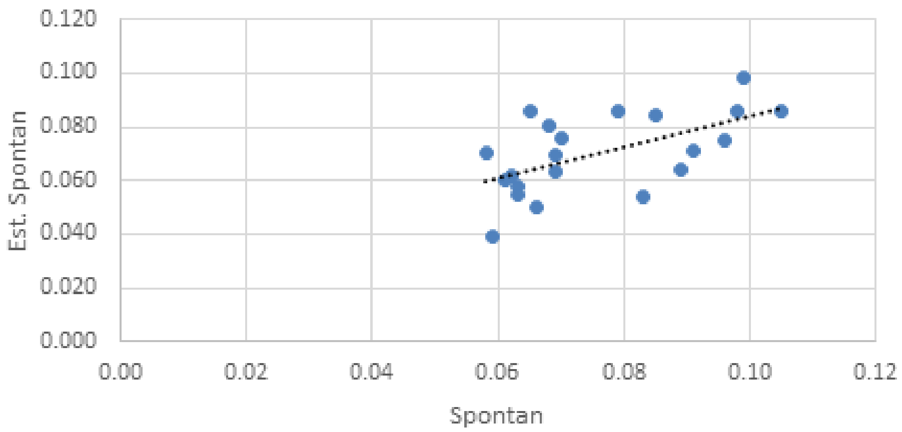
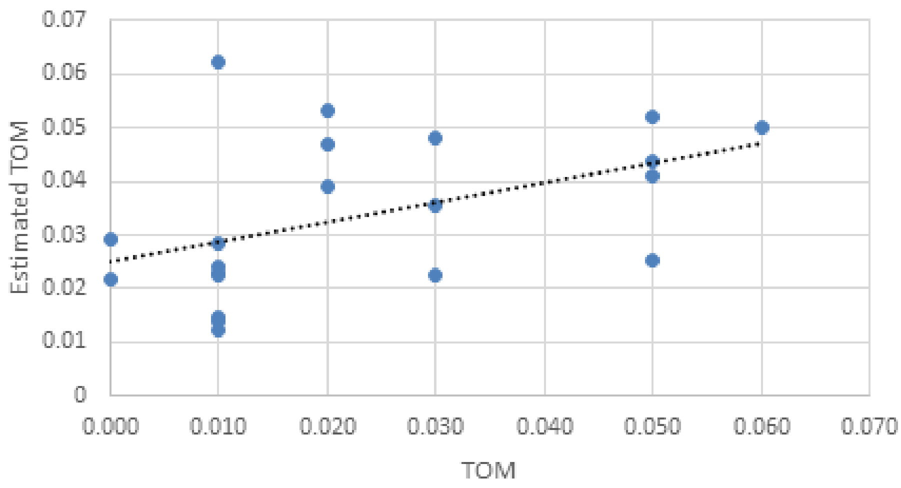


(c)

Figure A.11 : Scatter plot of estimated and measured data of company D: (a)TOM. (b)SOV. (c)Spontan.



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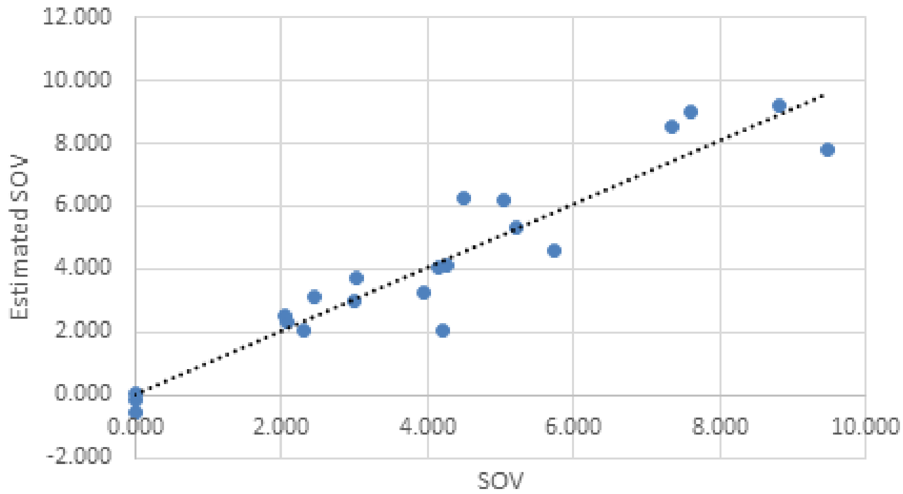

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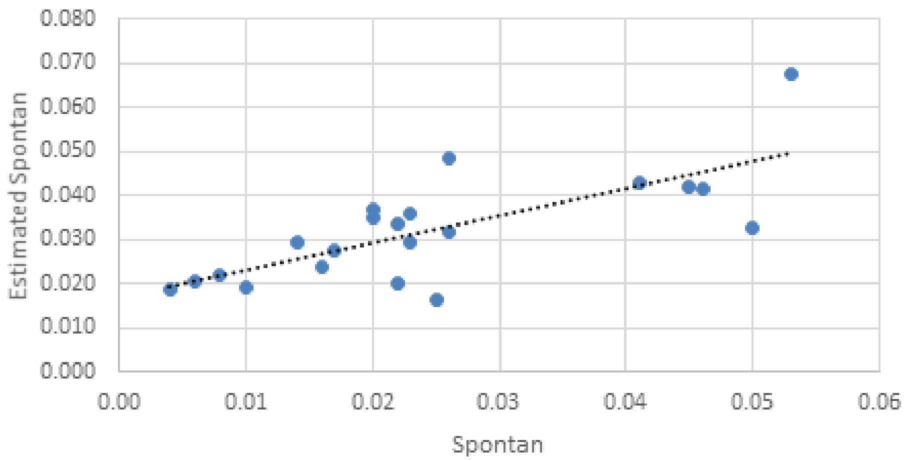
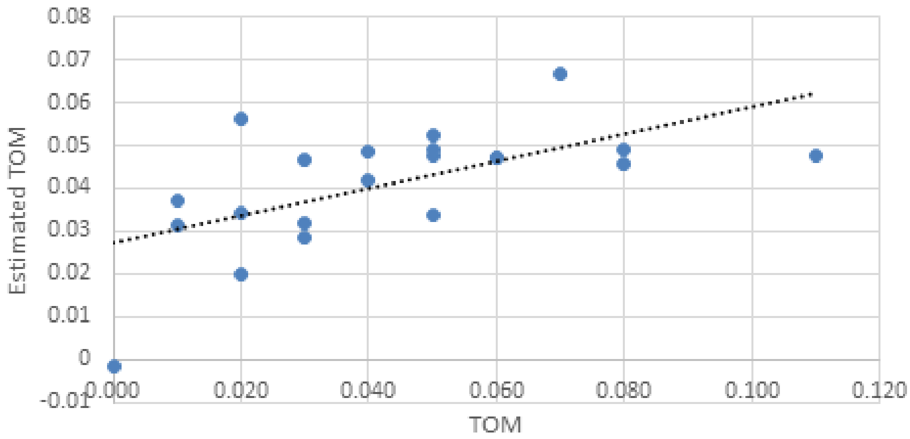


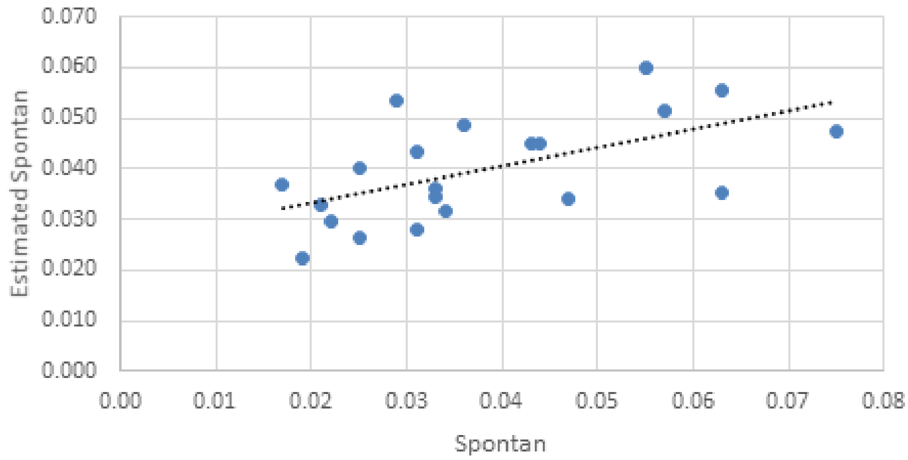
(c)

Figure A.12 : Scatter plot of estimated and measured data of company F: (a)TOM. (b)SOV. (c)Spontan.



(a)

(b)



(c)

Figure A.13 : Scatter plot of estimated and measured data of company G: (a)TOM. (b)SOV. (c)Spontan.

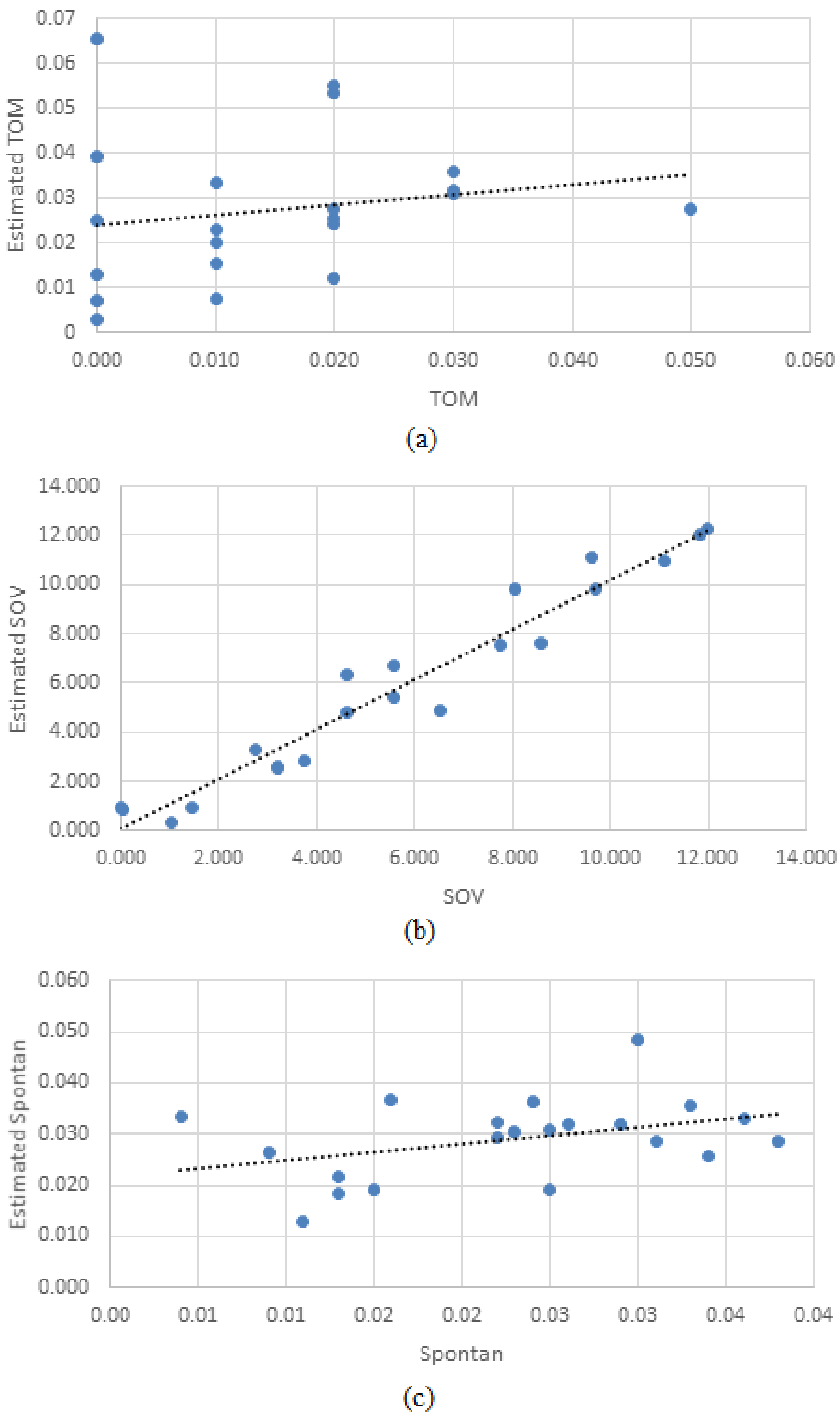
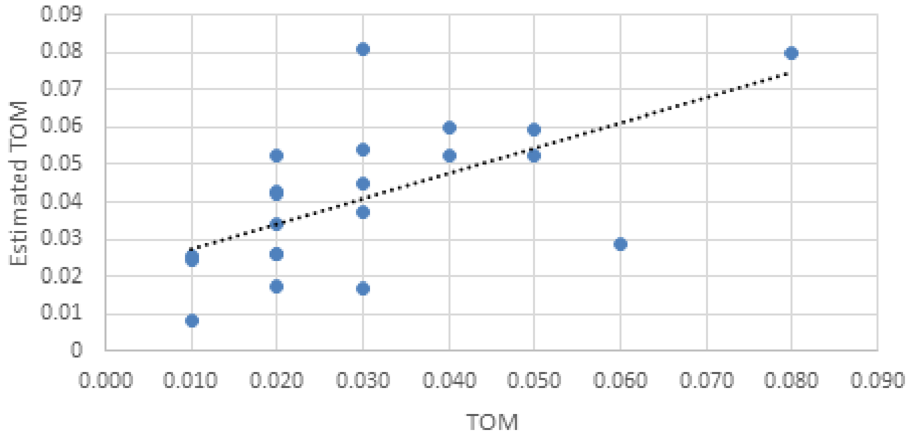
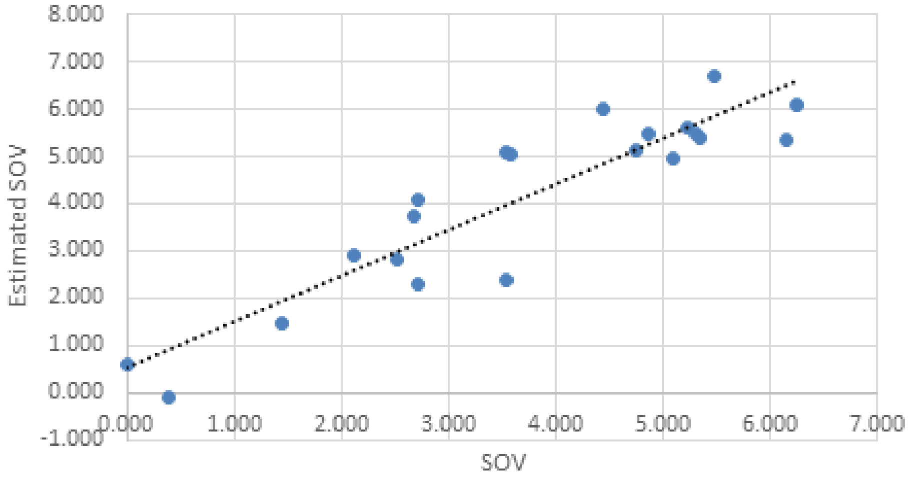


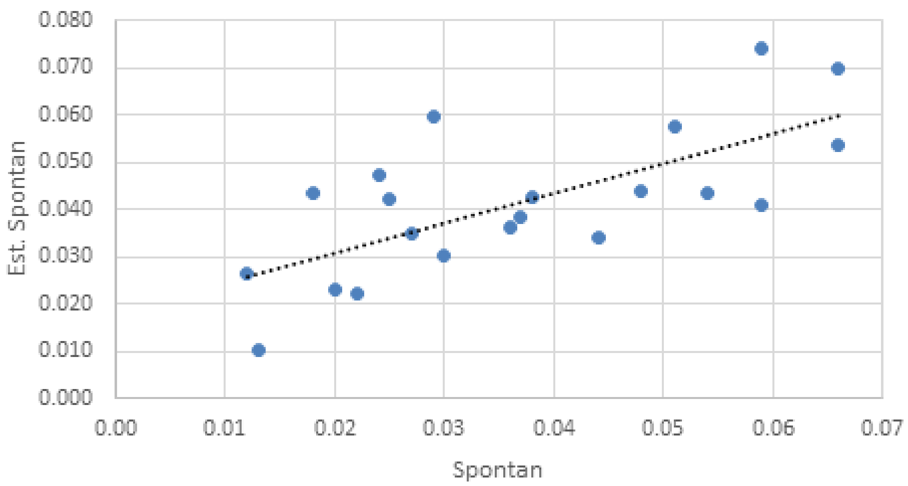
Figure A.14 : Scatter plot of estimated and measured data of company H: (a)TOM. (b)SOV. (c)Spontan.



(a)

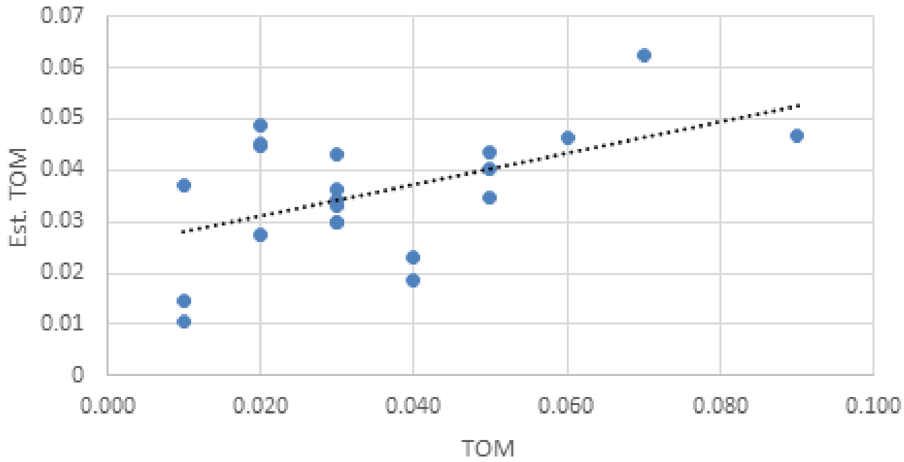


(b)

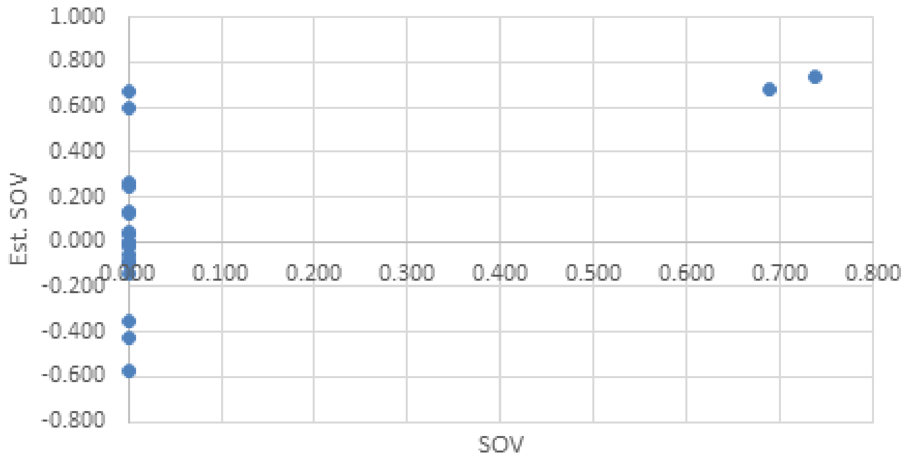


(c)

Figure A.15 : Scatter plot of estimated and measured data of company I: (a)TOM. (b)SOV. (c)Spontan.



(a)



(b)

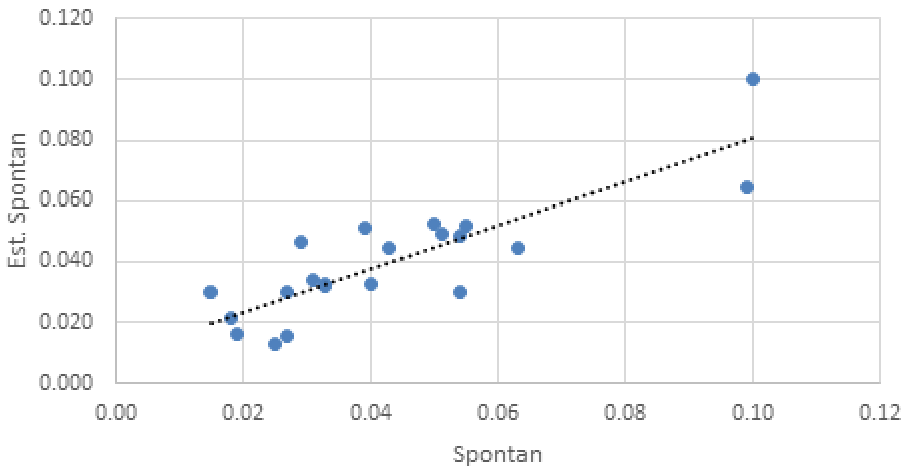


Figure A.16 : Scatter plot of estimated and measured data of company J: (a)TOM. (b)SOV. (c)Spontan.

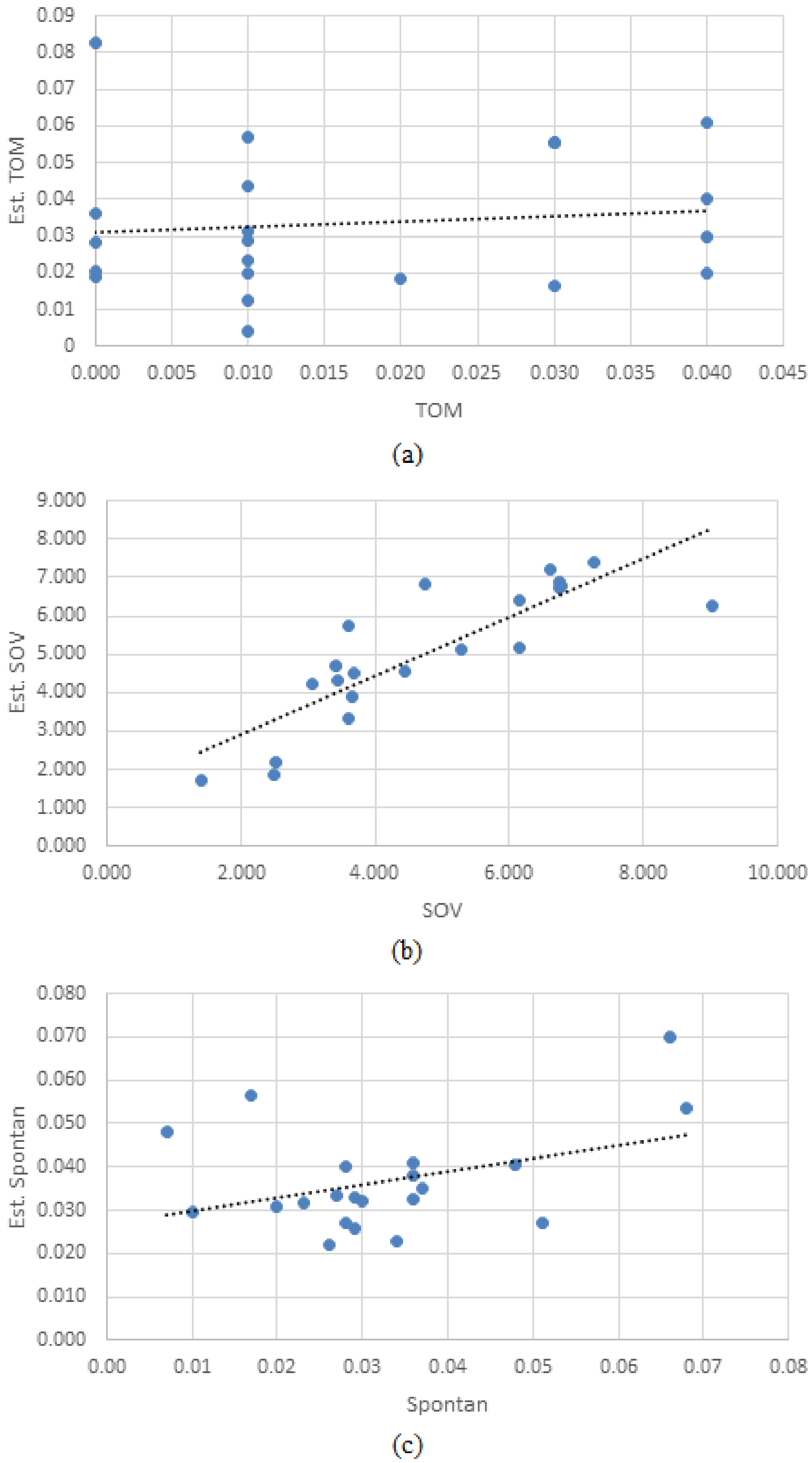
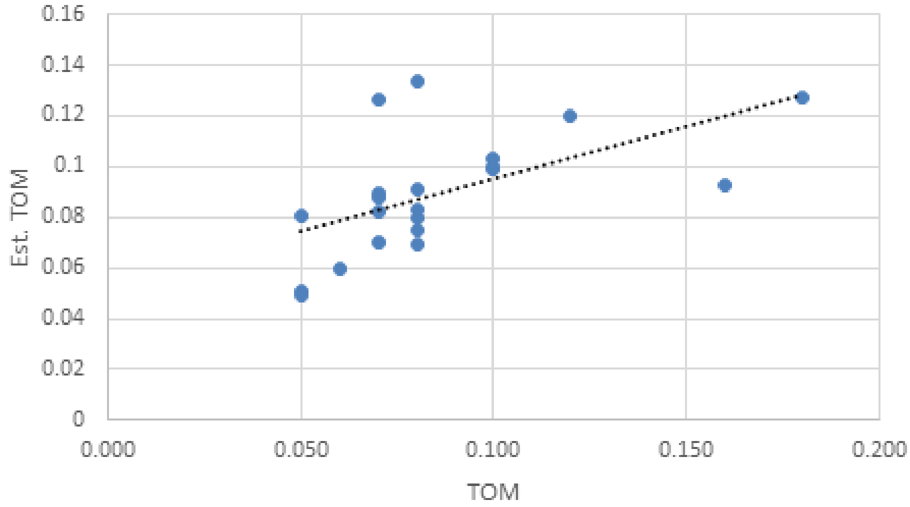
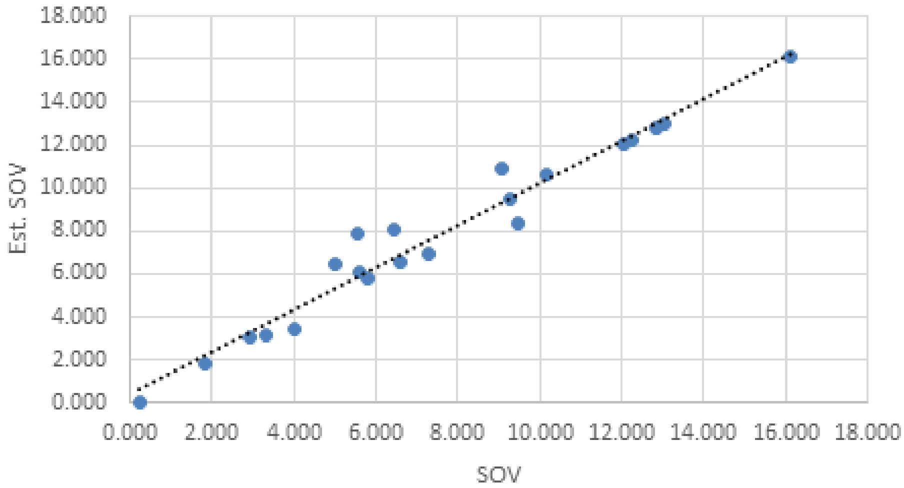


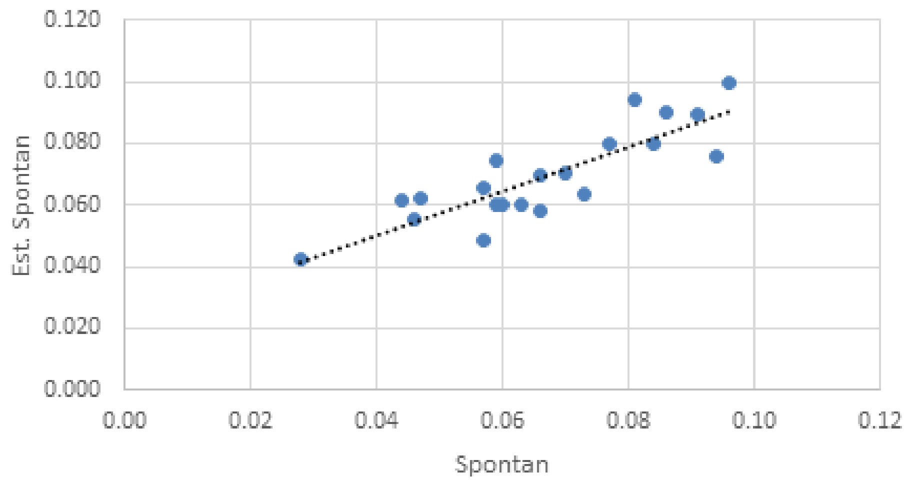
Figure A.17 : Scatter plot of estimated and measured data of company K: (a)TOM. (b)SOV. (c)Spontan.



(a)



(b)



(c)

Figure A.18 : Scatter plot of estimated and measured data of company L: (a)TOM. (b)SOV. (c)Spontan.

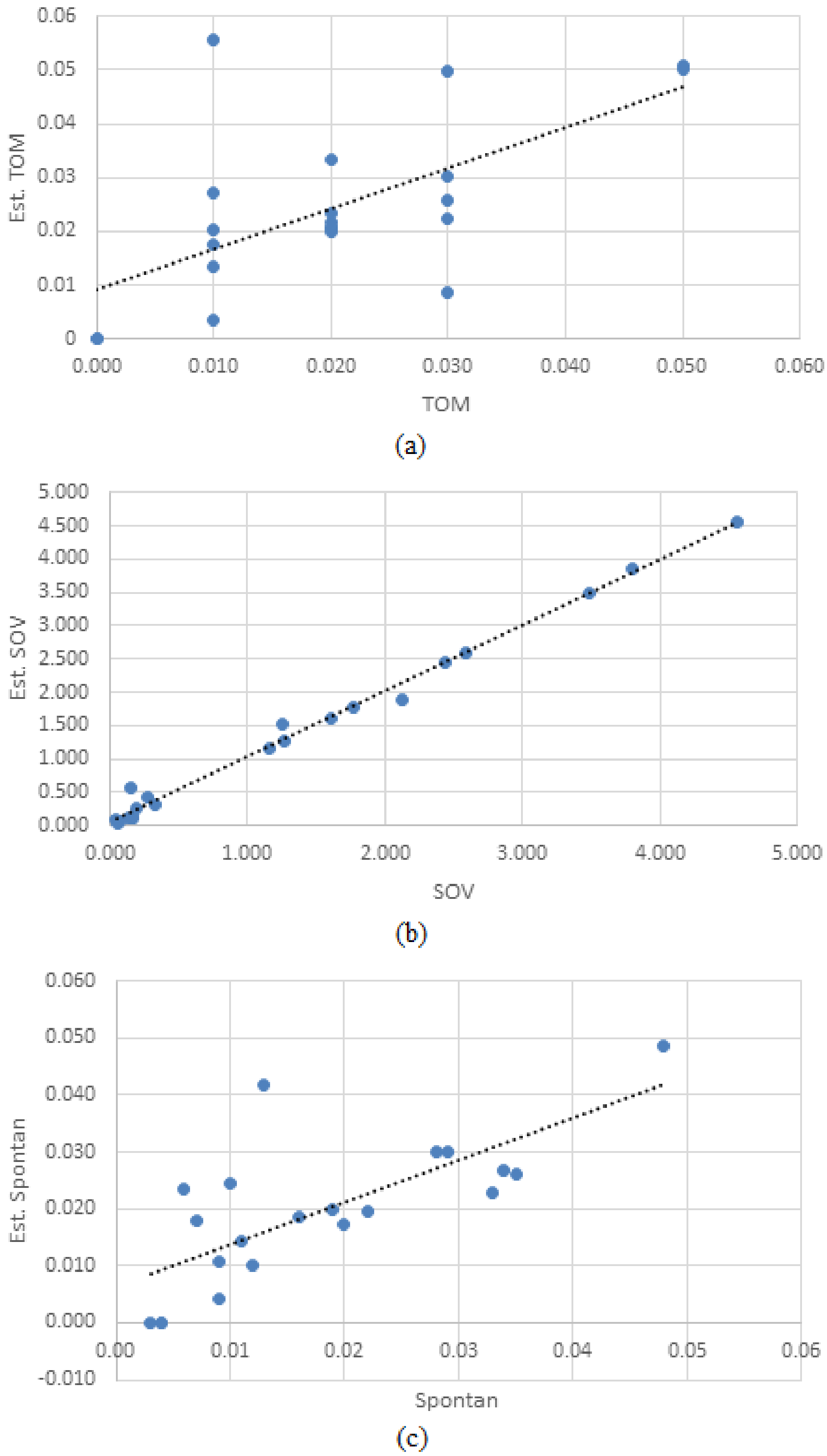
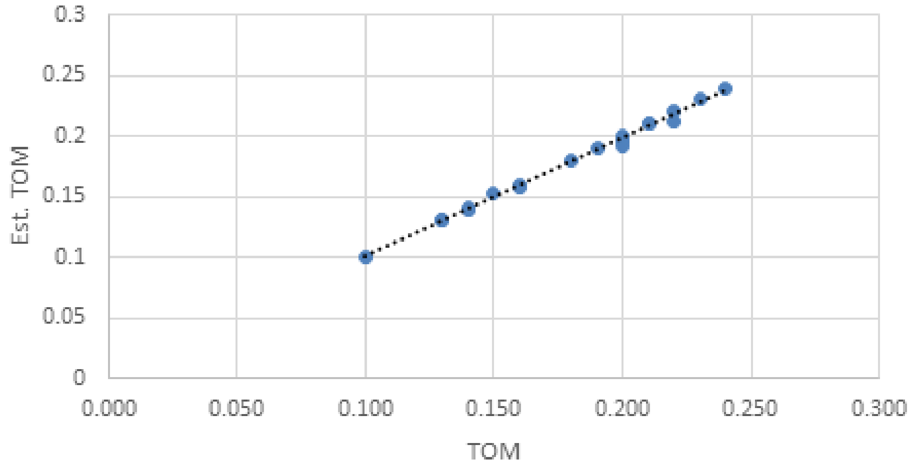
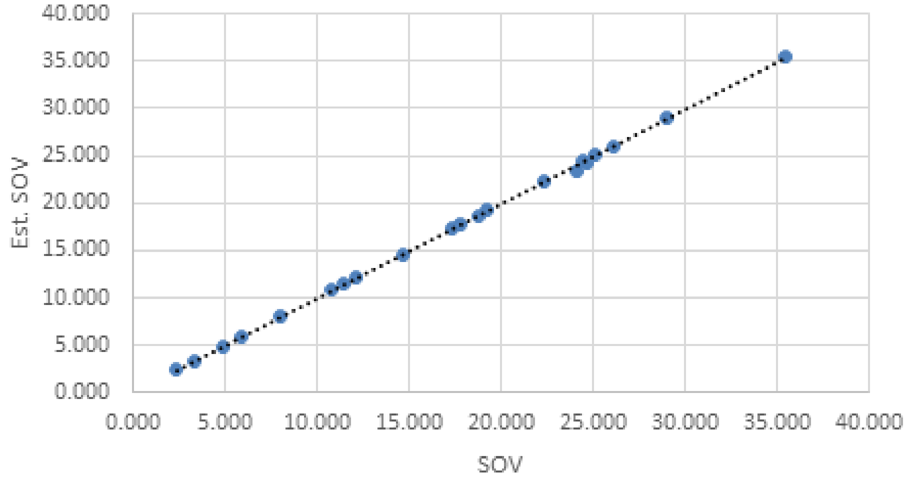


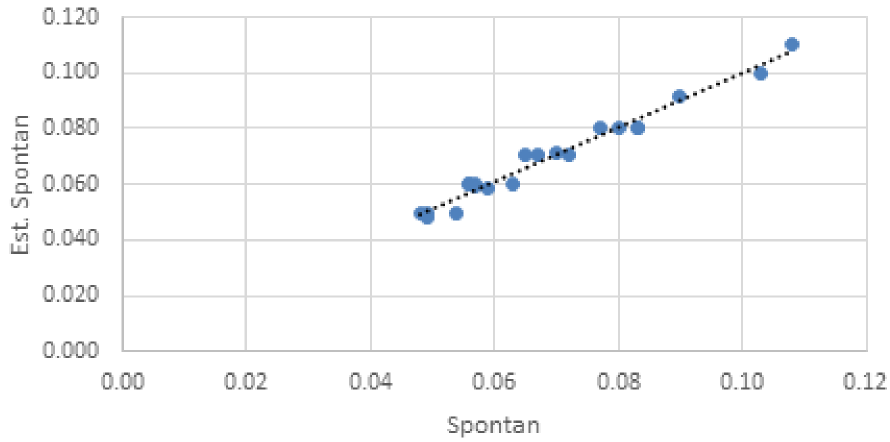
Figure A.19 : Scatter plot of estimated and measured data of company M: (a)TOM. (b)SOV. (c)Spontan.



(a)

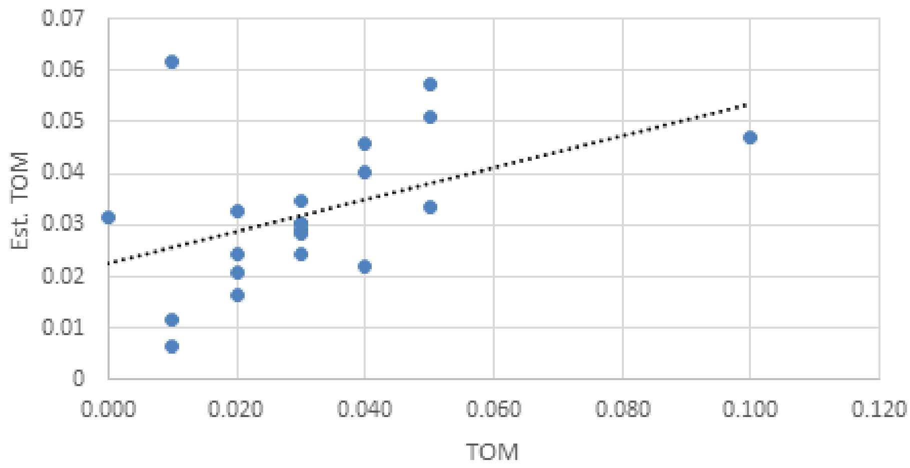


(b)

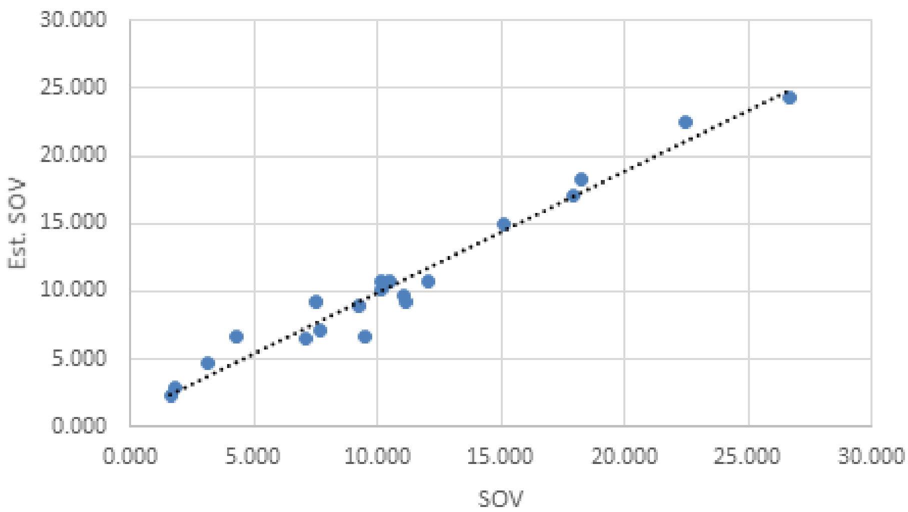


(c)

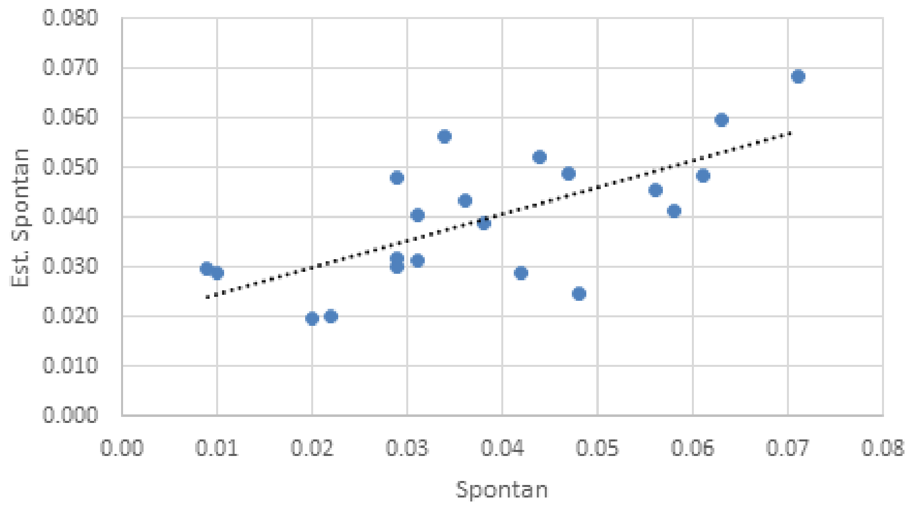
Figure A.20 : Scatter plot of estimated and measured data of company N: (a)TOM. (b)SOV. (c)Spontan.



(a)



(b)



(c)

Figure A.21 : Scatter plot of estimated and measured data of company O: (a)TOM. (b)SOV. (c)Spontan.

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List of Publications and Patents:

- **Fahmi, A.**, and Kahraman, C., 2016. Fuzzy Evaluation of Examinees through Multiple Choice Questions, *Journal of Computers & Education*, submitted.
- **Fahmi, A.**, Kahraman, C., and Bilen, U., 2016. ELECTRE I Method Using Hesitant Linguistic Term Sets: An Application to Supplier Selection, *International Journal of Computational Intelligence Systems*, 9(1), 153-167.
- **Fahmi, A.**, Dorostanian, A., Rezazadeh, H., and Ostadrahimi, A., 2013. An intelligent decision on support system (IDSS) for nutrition therapy: Infrastructure, decision support, and knowledge management design. *International Journal of Reliable and Quality E-Healthcare*, 2(4), 14-27.
- **Fahmi, A.**, and Kaya, T., Evaluation of alternative energy scenarios for Turkey using Bayesian network analysis, *International Symposium on Energy System Optimization*, November 9-10, 2015, Heidelberg, Germany.
- **Fahmi, A.**, Derakhshan, A., and Kahraman, C., Human resources management using interval valued intuitionistic fuzzy analytic hierarchy process, *IEEE International Conference on Fuzzy Systems: FUZZ-IEEE 2015*, August 2-5, 2015, Istanbul, Turkey.
- **Fahmi, A.**, and Kahraman, C., May the success be a matter of degree? Fuzzy examination and scoring through multiple choice questions, 27^{t}h *European Conference on Operational Research: EURO 2015*, programme handbook, p. 185, July 12-15, 2015, Glasgow, UK.