

CUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

**Modeling of Zeolite-Based Desiccant Wheel with Machine
Learning**

Alperen Burak GÜRÜK

Mechanical Engineering Department

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Modeling of Zeolite-Based Desiccant Wheel with Machine Learning

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ABSTRACT

The objective of this study is to model the desiccant wheel, which is frequently used in desiccant air-conditioning systems, using various machine learning and linear regression methods. The desiccant wheel with LT3 material was analyzed under 32,975 different input conditions using the manufacturer's software, considering 8 independent variables. The dataset generated was utilized to develop a total of 96 models, comprising 7 multiple linear regression models, 45 decision tree models, 12 support vector machine models, and 32 multilayer perceptron models. The models were evaluated based on various statistical metrics. Among the multiple linear regression models, the 3rd Degree Cross model demonstrated the best performance. It achieved RMSE values of 0.6018 °C and 0.1774 g/kg for process air outlet temperature and humidity ratio, with R² values of 0.9934 and 0.9972, respectively. The DT-28 model, the top-performing decision tree model, achieved RMSE values of 0.7196 °C and 0.1903 g/kg for temperature and humidity ratio, with R² values of 0.9977 and 0.9992, respectively. The SVM-5 model, the best among support vector machine models, achieved RMSE values of 0.3780 °C and 0.1082 g/kg for temperature and humidity ratio, with R² values of 0.9974 and 0.9989, respectively. The MLP-8 model, which provided the best results among the developed models, achieved RMSE values of 0.2059 °C and 0.0693 g/kg for temperature and humidity ratio, with R² values of 0.9994 and 0.9997, respectively.

Keywords: Desiccant wheel, LT3, Machine learning, Artificial Neural Network

Zeolit Tabanlı Nem Alıcı Tekerin Makine Öğrenmesi ile Modellenmesi

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ÖZ

Bu çalışmanın amacı kurutucu iklimlendirme sistemlerinde sıklıkla kullanılan nem alıcı rotorun, farklı makine öğrenmesi ve doğrusal regresyon yöntemleriyle modellenmesidir. LT3 malzemeli nem alıcı rotor için üretici firma yazılımı kullanılarak 8 farklı bağımsız değişkenle 32,975 farklı giriş koşulu için çıkış koşulu elde edilmiştir. Oluşturulan veri seti kullanılarak 7 çoklu doğrusal regresyon, 45 karar ağacı, 12 destek vektör makinesi ve 32 çok katmanlı algılayıcı modeli olmak üzere toplamda 96 farklı model geliştirilmiştir. Geliştirilen modeller farklı istatistiksel metrikler kullanılarak karşılaştırılmıştır. Çoklu doğrusal regresyon yöntemleri arasında en iyi sonucu 3. derece çapraz model vermiştir. Bu modelden üretilen proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 0.6018 °C ve 0.1774 g/kg ve R^2 değerleri ise sırasıyla, 0.9934 ve 0.9972'dir. Karar ağacı modellerinden en iyi performansı gösteren DT-28 kodlu modelin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 0.7196 °C ve 0.1903 g/kg, R^2 değerleri ise sırasıyla 0.9977 ve 0.9992 olarak bulunmuştur. SVM-5 kodlu model, destek vektör makinesi modellerinden en iyi sonucu vermiş olup, proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 0.3780 °C ve 0.1082 g/kg ve R^2 değerleri ise sırasıyla 0.9974 ve 0.9989 olarak belirlenmiştir. Geliştirilen bütün modeller arasında en iyi performansı gösteren MLP-8 kodlu modelin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 0.2059 °C ve 0.0693 g/kg ve R^2 değerleri ise sırasıyla 0.9994 ve 0.9997 olarak bulunmuştur.

Anahtar Kelimeler: Nem alıcı rotor, LT3, Regresyon, Makine öğrenmesi, Yapay sinir ağları

EXTENDED ABSTRACT

Air-conditioning is becoming increasingly important with the development of industry and the world population growth. Therefore, the amount of energy consumed for air-conditioning is growing day by day and is expected to increase further in the future. Vapor compression refrigeration systems, which have a very high share among cooling systems, consume a significant amount of energy and have negative environmental impacts. This situation directs researchers towards alternative cooling systems to vapor compression refrigeration systems, which are environmentally friendly and operate with low energy costs. Desiccant air-conditioning systems stand out as a good alternative to vapor compression systems, and although their initial cost is higher, their operating cost is lower. Moreover, since the energy requirement of desiccant air-conditioning systems is low-grade thermal energy, this energy need can be provided with solar thermal collectors. Additionally, integrating photovoltaic thermal collectors, which can simultaneously meet both the thermal energy requirement and the small amount of electrical energy needed for the system, is one of the current solutions.

The critical component of desiccant air-conditioning systems is the desiccant wheel, along with heat exchangers for heat recovery and various types of evaporative coolers. The role of desiccant wheel is to remove excess moisture from the process air taken from outside, thus removing moisture gains inside the conditioned space. The desiccant wheel consists of two sections through which the air to be dehumidified (process) and the air that will remove the moisture from the system (regeneration) sections. Both sections consist of numerous small channels coated with a desiccant material. As the process air passes through the desiccant wheel, a portion of the moisture it contains is absorbed by the desiccant material. The temperature of the air increases as its moisture decreases when exiting the desiccant wheel. Therefore, to reduce the air temperature to the desired level, heat exchangers used for heat recovery and different types of evaporative coolers that meet the main cooling load are integrated into the system.

Desiccant materials are divided as solid and liquid materials. Although liquid desiccant materials have high moisture absorption capacity, their high maintenance costs are their primary disadvantage. The low maintenance requirement and clean chemical composition of solid desiccant materials make them preferable to liquid desiccant systems. Moreover, since liquid desiccant materials are not practical to use in desiccant wheels which are generally used with solid desiccant materials.

Determining the output conditions of the desiccant wheel based on its input conditions is crucial for analyzing the performance of the system and the desiccant wheel. Furthermore, integrating developed models into various software (TRNSYS, EES, etc.) enables more practical performance analysis of the developed systems. The need for practical models for both system analysis and desiccant wheel performance analysis has increased research on this subject. Although there are

many performance and modeling studies in the literature for silica gel desiccant wheels, there are limited studies for LT3 desiccant wheels. This study aims to develop different models that accurately predict the process outlet temperature and humidity ratio of the LT3 desiccant wheel.

A comprehensive literature review identified eight different input parameters affecting the specification of outlet process air: process air inlet temperature and humidity ratio, regeneration air inlet temperature and humidity ratio, the rotational speed of the rotor, and the velocities of the process and regeneration air. By examining these eight different input parameters across various ranges, a total of 32,975 different operating conditions were determined and the output conditions were obtained for these input conditions using manufacturer software. A total of 96 different models were developed using this dataset with four methods: multiple linear regression, decision trees, support vector machines, and multilayer perceptron.

The developed models were compared based on statistical parameters such as root mean square error (RMSE), determination coefficient (R^2), and relative error. The determination coefficient, which ranges between 0 and 1, indicates increased model accuracy as it approaches 1. RMSE represents the deviation between predicted and actual values, with lower RMSE and higher R^2 values indicating an accurate model. While RMSE and R^2 provide a general overview of the model, relative error distributions must also be examined to detect anomalies.

Considering statistical parameters, the prediction performance of multiple linear regression models improved with the increase in the degree of the model or the inclusion of interaction terms. However, increasing the degree or adding interaction terms significantly increased the coefficients of models, complicating its reproduction ability. For instance, while the 1st Degree model has 8 coefficients, the 3rd Degree cross model has 121 coefficients. For the 1st Degree model, RMSE values for process air outlet temperature and humidity ratio were 2.2930 °C and 0.6948 g/kg, respectively, with R^2 values of 0.9000 and 0.9600. For the 3rd Degree Cross model, RMSE values for process air outlet temperature and humidity ratio were 0.6018 °C and 0.1774 g/kg, respectively, with R^2 values of 0.9934 and 0.9972. Additionally, the response surface model, with less number of coefficients (36) and high accuracy, had RMSE values of 1.0632 °C and 0.2998 g/kg, and R^2 values of 0.9800 and 0.9919 for process air outlet temperature and humidity ratio, respectively. The maximum error for process air outlet humidity ratio was 31.425% for the 3rd Degree Cross model and 12.188% for the response surface model.

In the decision tree method, the prediction performance of random forest models improved with the maximum number of splits. Moreover, keeping the maximum number of splits constant and increasing the number of trees enhanced model performance. "Curvature" and "interaction-curvature" predictors provided more accurate results than the "all splits" predictor in random forest models. The model coded, DT-18, developed using random forest model, provided the most accurate results, with RMSE values of 1.4764 °C and 0.4077 g/kg and R^2 values of 0.9603 and 0.9848 for process air outlet temperature and humidity ratio, respectively. For models developed with the

adaptive boosting, an increase in the number of splits negatively affected the prediction performance of models. The "all splits" predictor performed better than other predictors in adaptive boosting models. The DT-28 coded model had RMSE values of 0.7196 °C and 0.1903 g/kg and R^2 values of 0.9977 and 0.9992 for process air outlet temperature and humidity ratio, respectively. Among the models developed using the random tree, increasing the number of splits improved model performance, with the DT-43 coded model performing best. The DT-43 had RMSE values of 2.1256 °C and 0.5726 g/kg and R^2 values of 0.9283 and 0.9737 for process air outlet temperature and humidity ratio, respectively. The random tree model exhibited the worst prediction performance among all decision tree models developed.

For models developed under the support vector machine method, the kernel function was a primary factor affecting the prediction performance. Models developed with "Gaussian" and "rbf" kernel functions provided similar and highly accurate results. When using "SMO" and "ISDA" solvers, both solvers achieved similar prediction performance. In models with a polynomial kernel function, increasing the polynomial degree positively impacted prediction performance. The SVM-5 coded model provided the best results among support vector machine models, with RMSE values of 0.3780 °C and 0.1082 g/kg and R^2 values of 0.9974 and 0.9989 for process air outlet temperature and humidity ratio, respectively.

The models developed with multilayer perceptron method, four different training functions "trainlm", "trainbfg", "trainscg" and "trainoss" were used, with two hidden layers and four different neuron numbers of 10, 20, 30 and 40 in each hidden layer. In models with the "trainlm" training function (MLP-1 to MLP-8), increasing the hidden layer or neuron number improved model performance. However, the performance of the models developed with the "trainbfg" training function (from MLP-9 to MLP-16) did not improve in proportion to the increase in the number of hidden layers or neurons similar to the "trainlm" function. In models developed with the "trainscg" training function, an increase in neuron number improved prediction performance in all models except MLP-20 coded. Among models developed with the "trainoss" training function, MLP-29 coded (two hidden layers with 10 neurons each) and MLP-30 coded (two hidden layers with 20 neurons each) were compared. The best option for process air outlet temperature was MLP-29, while MLP-30 performed better for process air outlet humidity ratio.

The best results among all models developed with multiple linear regression, decision tree, support vector machine, and multilayer perceptron methods were obtained from the MLP-8 coded model. MLP-8 had RMSE values of 0.2059 °C and 0.0693 g/kg and R^2 values of 0.9994 and 0.9997 for process air outlet temperature and humidity ratio, respectively.

GENİŞLETİLMİŞ ÖZET

İklimlendirme sistemleri, endüstrinin gelişimi ve dünya nüfusunun artışıyla gün geçtikçe daha önemli hale gelmektedir. Bu sebepten, iklimlendirme için harcanan enerji miktarı her geçen gün artmakta ve önümüzdeki yıllarda da artmaya devam etmesi beklenmektedir. Dünyadaki soğutma sistemlerinde büyük bir paya sahip olan buhar sıkıştırırmalı soğutucuların enerji tüketimi fazla olmasının yanında çevreye olumsuz etkileri de vardır. Bu olumsuz noktalar bu alanda çalışan araştırmacıları buhar sıkıştırırmalı soğutucu sistemlere alternatif, çevre dostu ve düşük enerji maliyeti ile çalışan soğutma sistemlerine yönlendirmiştir. Son yıllarda buhar sıkıştırırmalı sistemlere iyi bir alternatif olarak, nem almalı iklimlendirme sistemleri öne çıkmıştır. Bu sistemlerin kurulum maliyeti buhar sıkıştırırmalı soğutuculu sistemlere göre daha fazla olsa da işletme maliyeti daha düşüktür. Ayrıca nem almalı iklimlendirme sistemlerinin temel enerji gereksinimi, düşük sıcaklıkta termal enerji olduğundan, ısı kolektörleri ile bu enerji ihtiyacı karşılanabilmektedir. Dahası, aynı anda hem ısı enerji gereksinimini hem de sistem için gerekli olan az miktarda elektrik enerjisini aynı anda karşılayabilen, fotovoltaik termal kolektörlerin (PVT) sisteme entegrasyonu, güncel çözümlerden biridir.

Nem almalı iklimlendirme sistemlerinde, sistemin en kritik ekipmanı olan nem alıcı rotorun yanında, ısı geri kazanımı için ısı değiştiricileri ve farklı tip buharlaştırmalı soğutucular da yer almaktadır. Nem alıcı rotorun görevi, dışarıdan alınan proses havasındaki fazla nemi uzaklaştırarak, mahal içerisindeki nem kazancının uzaklaştırılmasıdır. Nem alıcı malzeme, nemi alınacak havanın (proses) ve nemi nem alıcı rotordan uzaklaştıracak havanın (rejenerasyon) geçtiği iki bölümden oluşmaktadır. Her iki bölüm de üzerine nem alıcı bir maddenin tutturulduğu küçük çaplı çok fazla sayıda kanalcıktan oluşmaktadır. Proses havası nem alıcı rotordan geçerken, içerdiği nemin bir miktarı nem alıcı madde tarafından adsorbe edilir. Rotordan çıkan havanın nemi azalırken sıcaklığı artmaktadır. Bu sebeple havanın sıcaklığını istenilen noktaya düşürebilmek için birçok iklimlendirme sisteminde ısı geri kazanımı için kullanılan ısı değiştiricileri ve asıl soğutma yükünü karşılayan farklı tipte buharlaştırmalı soğutucular sisteme entegre edilmektedir.

Nem alıcı malzemeler katı ve sıvı olmak üzere ikiye ayrılır. Sıvı nem alıcı malzemeler yüksek nem alma yeteneğine sahip olsa da yüksek bakım maliyetleri temel dezavantajlarıdır. Katı nem alıcı malzemelerin az bakım gereksinimi ve temiz kimyasal içeriğine sahip olması, sıvı nem alıcı sistemlerden daha ön plana çıkmalarına sebep olmaktadır. Buna ek olarak sıvı nem alıcı malzemelerin, nem alıcı rotorda kullanımı pratik olmadığından nem alıcı rotorlar genellikle katı nem alıcı malzemeler ile birlikte kullanılır.

Nem alıcı rotorun giriş koşullarına göre çıkış koşullarının belirlenmesi sistemin ve nem alıcı rotorun performans analizinin yapılması açısından önemlidir. Ayrıca geliştirilen modellerin çeşitli yazılımlara (TRNSYS, EES vb.) entegre edilebilmesi, geliştirilen sistemlerin performans analizlerinin daha pratik yapılmasını sağlar. Hem sistem analizi hem de rotorun performans analizi

için pratik model ihtiyacı, araştırmacıların bu konuda çalışmalarını artırmıştır. Literatürde silika jel nem alıcı rotor için birçok performans ve modelleme çalışması olmasına rağmen LT3 nem alıcı rotor için sınırlı sayıda çalışma mevcuttur. Bu çalışmada, LT3 nem alıcı rotorun proses çıkış sıcaklığı ve nemini yüksek doğrulukta tahmin eden farklı modellerin geliştirilmesi amaçlanmıştır.

Yapılan kapsamlı literatür taraması ile nem alıcı rotorun proses havası çıkış sıcaklığı ve nemine etki eden bağımsız değişken olarak proses havası giriş sıcaklığı ve nemi, rejenerasyon havası giriş sıcaklığı ve nemi, rotorun dönme hızı, proses ve rejenerasyon havasının hızları olmak üzere sekiz farklı giriş parametresi belirlenmiştir. Belirlenen sekiz farklı giriş parametresi farklı aralıklarda incelenerek üretici yazılımı ile toplamda 32,975 adet farklı çalışma koşulu elde edilmiştir. Elde edilen veri seti ile çoklu doğrusal regresyon, karar ağacı, destek vektör makinesi ve çok katmanlı algılayıcı olmak üzere dört metotta toplam 96 farklı model geliştirilmiştir.

Çoklu doğrusal regresyon metodu ile farklı dereceden ve bağımsız değişkenlerin birbirleri ile etkileşimlerinin dahil edildiği 7 farklı model geliştirilmiştir. Karar ağacı metodu için rastgele orman, rastgele ağaç ve uyarlamalı artırma ana başlıkları altında 45 farklı model geliştirilmiştir. Bu modeller için maksimum ağaç, maksimum dallanma ve tahminleyici gibi farklı parametrelerin etkileri incelenmiştir. Destek vektör makinesi metodu içerisinde dört farklı kernel fonksiyonu ile modelleme yapılmıştır. Bu fonksiyonların arasında yer alan polinom kernel fonksiyonu modellerinin, derecesi değiştirilerek toplamda 12 farklı destek vektör makinesi modeli elde edilmiştir. Çok katmanlı yapay sinir ağı metodunda ise eğitim fonksiyonu, gizli katman sayısı ve her bir katmandaki nöron sayısı olmak üzere üç farklı parametre ile 32 farklı model geliştirilmiştir.

Elde edilen modeller kök ortalama kare hatası (RMSE), belirleme katsayısı (R^2) ve bağıl hata gibi istatistiksel parametrelere göre karşılaştırılmıştır. Sıfır ile bir arasında değer alabilen belirleme katsayısı, bire yaklaştıkça modelin doğruluğu artmaktadır. Kök ortalama kare hatası ise tahmin verileri ile gerçek veriler arasındaki sapmayı temsil etmektedir. Düşük bir kök ortalama kare hatası ve yüksek belirleme katsayısı iyi bir model elde edildiğini göstermektedir. Kök ortalama kare hatası ve belirleme katsayısı değerleri her ne kadar modelin genel hatları hakkında bilgi verse de aşırı koşullarda kötü tahminler gözlemlenebilmektedir. Bu anormalliklerin tespit edilebilmesi için bağıl hata dağılımlarının da incelenmesi gerekmektedir.

İstatistiksel parametreler göz önüne alındığında, çoklu doğrusal regresyon modellerinin tahmin performansının, modelin derecesinin artışı veya çapraz terimlerin eklenmesi ile arttığı görülmüştür. Ancak derecenin artması veya çapraz terimlerin eklenmesi modelin katsayısında ciddi bir artışa neden olmaktadır. Örneğin birinci derece modelin 8 katsayısı varken, üçüncü derece çapraz modelin ise 121 katsayısı vardır ve bu modelin kullanımını zorlaştırmaktadır. Birinci derece modelin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 2.2930 °C ve 0.6948 g/kg iken, R^2 değerleri ise sırasıyla 0.9000 ve 0.9600 olarak elde edilmiştir. Üçüncü derece çapraz modelin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 0.6018 °C ve 0.1774 g/kg, R^2 değerleri ise sırasıyla 0.9934 ve 0.9972 olarak gözlemlenmiştir. Buna ek olarak üçüncü derece çapraz

modeline kıyasla daha az katsayıya (36) sahip ve yüksek doğrulukta sonuç veren yanıt yüzey modelinin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 1.0632 °C ve 0.2998 g/kg, R^2 değerleri ise sırasıyla 0.9800 ve 0.9919'dur. Ayrıca proses havası çıkış nemi için maksimum hata üçüncü derece çapraz model için %31.425 mertebesindeyken, yanıt yüzey modelinde ise %12.188 olarak gözlemlenmiştir.

Karar ağacı metodunda, rastgele orman modellerinin tahmin performansının maksimum bölünme sayısı ile iyileştiği görülmüştür. Ayrıca modelin maksimum bölünme sayısı sabit tutulduğunda, ağaç sayısının artışı ile modelin performansının arttığı görülmüştür. “Eğrilik” ve “etkileşim-eğriliği” tahmin edicileri, “tüm ayırma” tahmin edicisine göre rastgele orman modellerinde daha doğru sonuç vermiştir. Geliştirilen rastgele orman modellerinden en doğru sonucu DT-18 kodlu model vermiştir. DT-18 modelinin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 1.4764 °C ve 0.4077 g/kg iken R^2 değerleri sırasıyla 0.9603 ve 0.9848'dir. Uyarlamalı artırma ile geliştirilen modeller için ise bölünme sayısındaki artışın modelin tahmin performansını düşürdüğü görülmüştür. “Tüm ayırma” tahmin edicisi uyarlamalı artırma modelleri için diğer tahmin edicilere kıyasla daha iyi tahmin performansı sergilemiştir. DT-28 kodlu modelin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 0.7196 °C ve 0.1903 g/kg, R^2 değerleri ise sırasıyla 0.9977 ve 0.9992'dir. Rastgele ağaç modeli ile geliştirilen modellerdeki bölünme sayısındaki artışın, modelin performansını artırdığı görülmüştür. Rastgele ağaç modelleri arasında en iyi sonucu DT-43 kodlu model vermiştir. DT-43 modelinin proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 2.1256 °C ve 0.5726 g/kg, R^2 değerleri ise sırasıyla 0.9283 ve 0.9737'dir. Rastgele ağaç modeli, geliştirilen tüm karar ağacı modelleri arasında en kötü performansı sergilemiştir.

Destek vektör makinesi metodu ile geliştirilen modellerin tahmin performansına etki eden parametrelerin başında kernel fonksiyonu gelmektedir. “Gaussian” ve “rbf” kernel fonksiyonları ile geliştirilen modeller birbirlerine yakın ve yüksek doğrulukta sonuç vermişlerdir. Çözümleyici olarak “SMO” ve “ISDA” kullanılırken, bu iki çözümleyici birbirlerine yakın değerlerde tahmin performansına sahiptir. Kernel fonksiyonu polinom olan modellerde, polinom derecesindeki artış, modelin tahmin performansını olumlu yönde etkilemiştir. SVM-5 kodlu model ise destek vektör makinesi ile geliştirilen modeller arasında en iyi sonucu vermiş olup, proses havası çıkış sıcaklığı ve nemi için RMSE değerleri sırasıyla 0.3780 °C ve 0.1082 g/kg, R^2 değerleri ise sırasıyla 0.9974 ve 0.9989'dir.

Çok katmanlı algılayıcı modelleri için ise “trainlm”, “trainbfg”, “trainscg” ve “trainoss” olmak üzere dört farklı eğitim fonksiyonu, iki gizli katman ve her gizli katmandaki nöron sayısı 10, 20, 30 ve 40 olmak üzere dört farklı nöron sayısında çalışma yapılmıştır. “Trainlm” eğitim fonksiyonuna sahip modellerde (MLP-1'den MLP-8'e) gizli katman veya nöron sayısındaki artışın modelin performansını artırdığı görülmüştür. Ancak “trainbfg” eğitim fonksiyonu ile geliştirilen modellerin (MLP-9'dan MLP-16'ya) performansında, “trainlm” fonksiyonundakine benzer gizli

katman veya nöron sayısındaki artışla orantılı bir iyileşme gözlemlenmemiştir. “Trainsecg” eğitim fonksiyonu ile geliştirilen modellerde, nöron sayısındaki artış, MLP-20 kodlu model dışındaki tüm modellerin tahmin performansını artırmıştır. “Trainoss” eğitim fonksiyonu ile geliştirilen modeller arasında iki gizli katmanı ve her gizli katmanında 10 nöronu olan MLP-29 ve iki gizli katmanı ve her gizli katmanında 20 nöronu olan MLP-30 kodlu modeller karşılaştırılmıştır. Proses havasının çıkış sıcaklığı göz önüne alındığında, MLP-29 kodlu model daha iyi sonuç vermiştir. Diğer taraftan, proses havasının çıkış nemi göz önüne alındığında, MLP-30 kodlu model daha başarılıdır.

Çoklu doğrusal regresyon, karar ağacı, destek vektör makinesi ve çok katmanlı algılayıcı metotları ile geliştirilen tüm modeller arasında en iyi sonuçlar MLP-8 kodlu modelden elde edilmiştir. Bu modelin istatistiksel parametreleri incelendiğinde proses havası çıkış sıcaklığı ve nemi için RMSE değerlerinin sırasıyla 0.2059 °C ve 0.0693 g/kg iken R^2 değerlerinin ise sırasıyla 0.9994 ve 0.9997 olduğu gözlemlenmiştir.



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SYMBOLS AND ABBREVIATIONS

APS	: Announced Pledges Scenario
COP	: Coefficient of Performance
COP _{lat}	: Latent Coefficient of Performance
CS	: Conditioned space
DAC	: Desiccant Air-Conditioning
DEC	: Direct Evaporative Cooler
DPIEC	: Dew-Point Indirect Evaporative Cooler
DT	: Decision Tree
DW	: Desiccant Wheel
EMDE	: Emerging Market and Developing Economies
H	: Regeneration heater
HVAC	: Heating Ventilation Air-Conditioning
HX	: Sensible Heat Exchanger
IDEC	: Indirect Evaporative Cooler
IEA	: International Energy Agency
ML	: Machine Learning
MLP	: Multilayer Perceptron
MRC	: Moisture Removal Capacity
N	: Rotational Speed
p	: Number of independent variables
R ²	: Coefficient of Determination
RE	: Relative Error
RMSE	: Root Mean Square Error
SER	: Sensible Energy Ratio
SMRC	: Specific Moisture Removal Capacity
STEPS	: Stated Policies Scenario
SVM	: Support Vector Machine
T _{p,in}	: Process air inlet temperature
T _{r,in}	: Regeneration air inlet temperature
VCR	: Vapor Compression Refrigeration
V _{p,in}	: Process air velocity
V _{r,in}	: Regeneration air velocity
$\omega_{p,in}$	: Process air inlet humidity ratio
$\omega_{r,in}$	: Regeneration air inlet humidity ratio
β	: Coefficient of regression

x : Independent variable



1. INTRODUCTION

According to International Energy Agency (IEA) reports, 5 billion out of 7.5 billion people worldwide require significant cooling. In the early 2000s, approximately 20% of households globally had air conditioners, a figure that has now increased to 35% (IEA, 2022). The escalation in living standards, coupled with rising average global temperatures due to climate change, is driving higher energy use for space cooling. Furthermore, technological advancements are raising occupant comfort expectations, making the provision of suitable temperature and humidity conditions essential (IEA, 2017). Heating, ventilation, and air-conditioning (HVAC) systems, which ensure indoor comfort, are crucial in meeting this growing demand (ASHRAE, 2003). Cooling, in particular, accounts for a significant portion of a building's energy consumption, as shown in Figure 1.1 Each year, cooling demand is increasing in both advanced and emerging markets and developing economies (EMDE), and this trend is expected to continue (IEA, 2022).

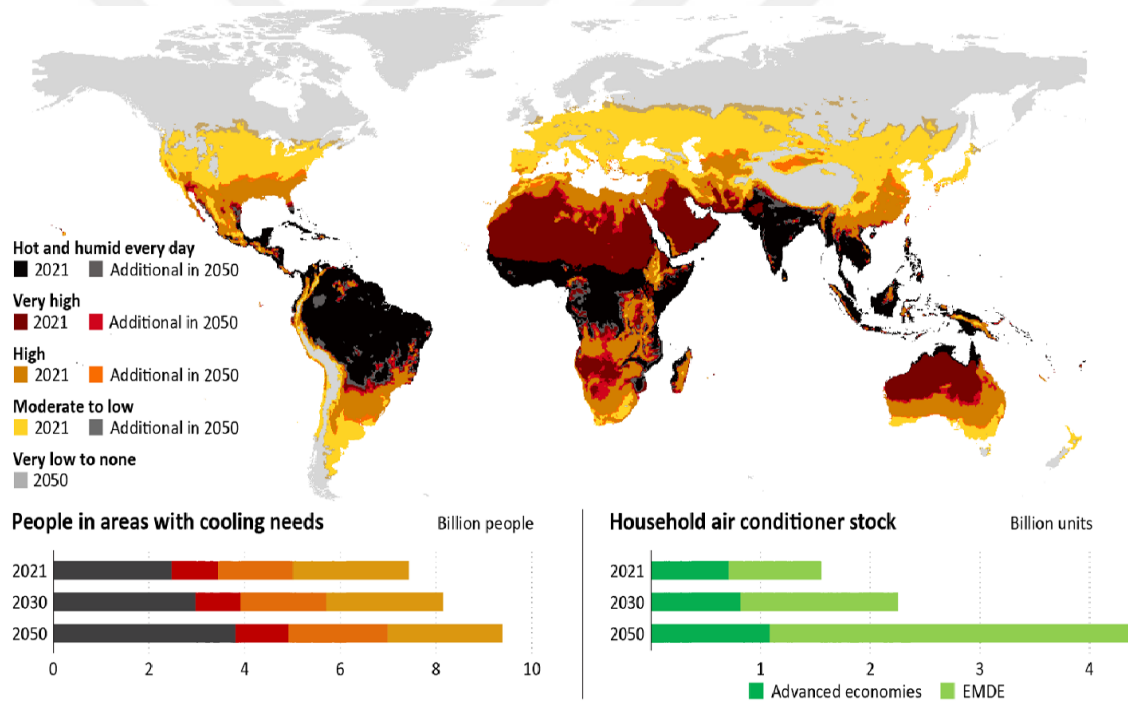


Figure 1.1. Space cooling needs and household air conditioner stocks in the STEPS, (2021-2050) (IEA, 2022).

According to the two different scenarios developed by the IEA, namely the Stated Policies Scenario (STEPS) and the Announced Pledges Scenario (APS), space cooling demand is expected to continue increasing in all regions of the world in the coming years (Figure 1.2). Therefore, desiccant air-conditioning (DAC) systems, which primarily consume thermal energy and require less electrical energy, have been positioned in the literature as an alternative air-conditioning system to those that use high-quality electrical energy (Sahlot and Riffat, 2016).

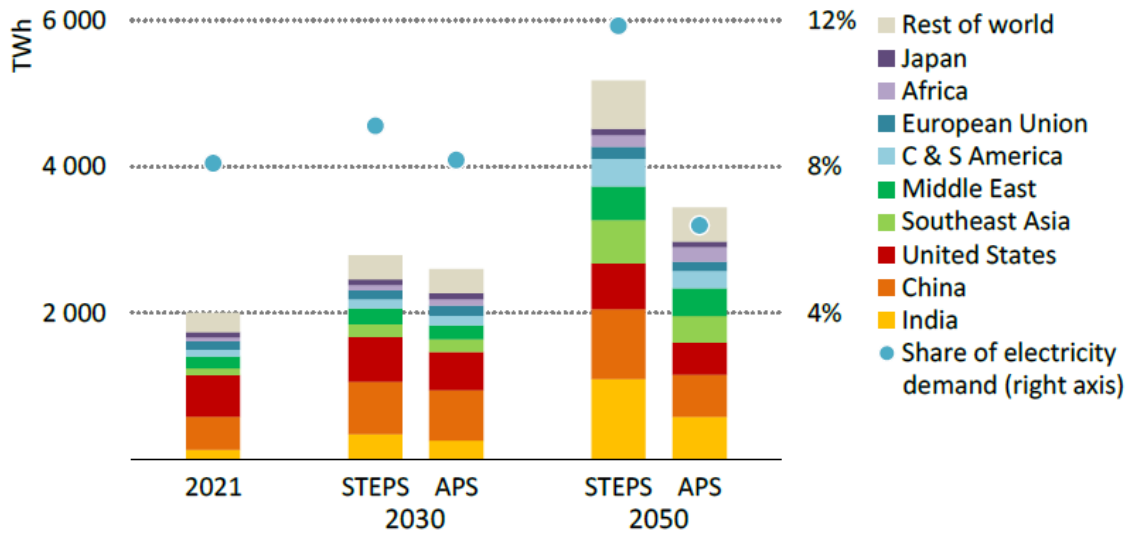


Figure 1.2. Space cooling demand by region in the STEPS and APS, 2021-2050 (IEA, 2022).

1.1. Systems Utilized in Climatization

Air-conditioning involves providing air under controlled conditions, such as maintaining air within a specific temperature range and humidity level. These ranges vary based on the desired conditions. For instance, to ensure proper growth of orchids in a greenhouse, the relative humidity should be maintained between 50% and 70%, with a temperature range of approximately 18 to 26 °C (Mandal and Ganguly, 2022). Meanwhile, for human comfort standards, the room's relative humidity should be around 50% and the temperature approximately 26 °C (ASHRAE, 2003).

In modern comfort cooling applications, vapor compression refrigeration (VCR) systems are widely used worldwide (Alsouda et al., 2023). Although these systems can have various configurations, the basic cycle (Figure 1.3) operates as follows. Initially, ambient air is introduced into the evaporator section (1→2) of the vapor compression system, where it is cooled to its dew point. Upon reaching the dew point, the moisture in the air begins to condense and is subsequently expelled. Following the cooling process, the air is reheated to attain the desired supply temperature and relative humidity (2→3), if necessary, before being delivered to the conditioned space (CS). Consequently, VCR systems are inherently limited in their ability to provide controlled dehumidification. Moreover, the reheating of the cooled process air to achieve suitable conditions results in a reduction in the system's coefficient of performance (COP).

The Pennington cycle (Pesaran et al., 1992), shown in Figure 1.4, is a conventional desiccant air-conditioning system. The air-conditioning process operates as follows: First, the process air passes through the desiccant wheel (1→2), where its temperature increases and humidity ratio decreases due to the desiccant material's moisture absorbing properties.

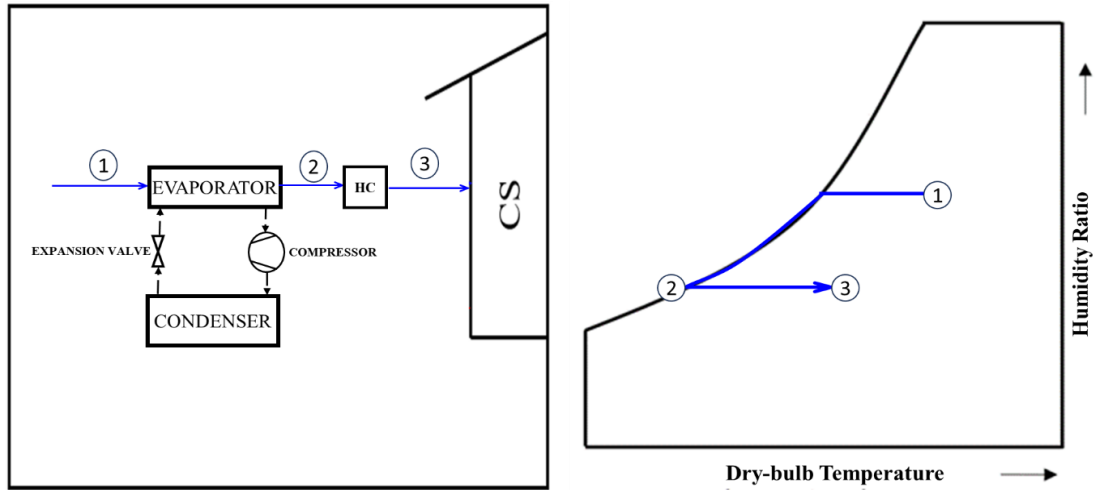


Figure 1.3. Vapor compression refrigeration air-conditioning system and its psychrometric chart.

Next, the air passes through a heat exchanger for heat recovery (2→3), which lowers the air temperature while keeping the humidity ratio constant. The process air then enters the direct evaporative cooler (3→4), where water sprayed into the air evaporates, thereby absorbing heat and increasing humidity ratio. This step cools the air while raising its humidity ratio. Finally, the conditioned air is then delivered to the conditioned space (4→5) (Jani et al., 2016).

Air from the conditioned space (5→6) returns to the direct evaporative cooler for reuse in the regeneration section (6→7). Here, the regeneration air's temperature is reduced, and its humidity ratio is increased. The regeneration air then moves to the heat exchanger to cool the process air (7→8), absorbing heat in the process. Afterward, the regeneration air passes through a heater (8→9), increasing its temperature to enhance dehumidification. Finally, the heated regeneration air passes through the desiccant wheel's regeneration side, removing moisture from the wheel and expelling it into the atmosphere.

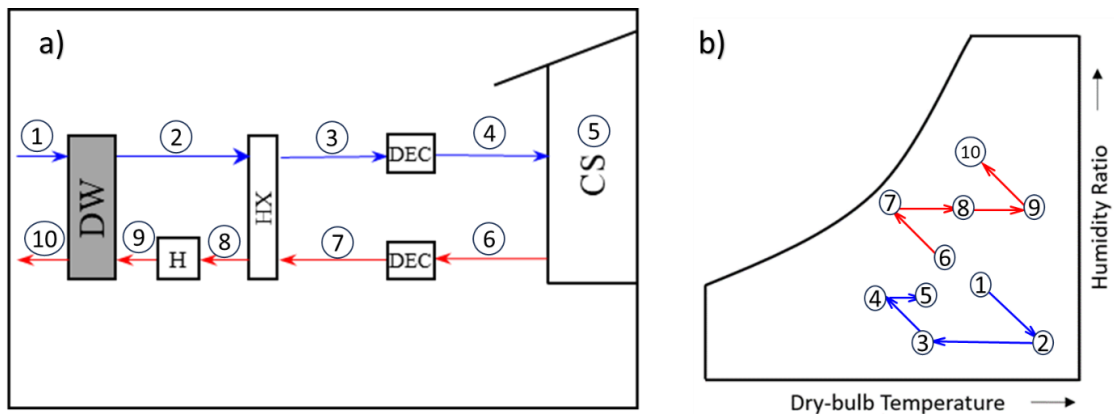


Figure 1.4. Schematic (a) and psychrometric chart (b) of Pennigton cycle.

1.2. Comparison of DAC and VCR Systems.

Carbon emissions need to be reduced to prevent ozone layer depletion (Fang et al., 2019). Desiccant air-conditioning (DAC) systems are preferable to vapor compression refrigeration (VCR) systems due to their compatibility with renewable energy sources. Jani (2019) highlighted several advantages and disadvantages of DAC systems. The advantages include their ability to operate with low-grade thermal energy, environmental friendliness due to the absence of harmful refrigerants used in VCR systems, low operating costs, and high dehumidification capacities. However, the disadvantages include their complexity and high initial costs.

1.3. Components of Desiccant Air-conditioning Systems

DAC systems generally employ the following components: desiccant wheel (DW), regeneration heater (H), sensible heat exchanger (HX), direct evaporative cooler (DEC), indirect evaporative cooler (IDEC), or dew-point indirect evaporative cooler (DPIEC). Renewable energy is preferred as the heat source for regeneration in heaters (Jani et al., 2016). Cooling is provided by DEC, IDEC, DPIEC, or VCR systems. The desiccant wheel handles humidity removal, while only electric energy is used by the rotor that rotates the desiccant wheel (Sultan et al., 2015).

The desiccant wheel also referred to as the desiccant rotor and depicted in Figure 1.5, serves as the backbone of desiccant air-conditioning systems, where the crucial dehumidifying process occurs. This wheel is divided into two distinct sections: the process side and the regeneration side. On the process side, the desiccant wheel absorbs humidity from the process air, consequently warming it. Following this dehumidification, the process air advances to the subsequent device in the system. Simultaneously, the desiccant wheel, driven by a motor, rotates continuously, ensuring that the process section transitions to the regeneration side. Here, the regeneration air, preheated by a heater to enhance its dehumidification capacity, purges the accumulated moisture from the desiccant material. Ultimately, the moisture-laden regeneration air is expelled into the atmosphere, thus completing the cycle (Olmuş et al., 2023).

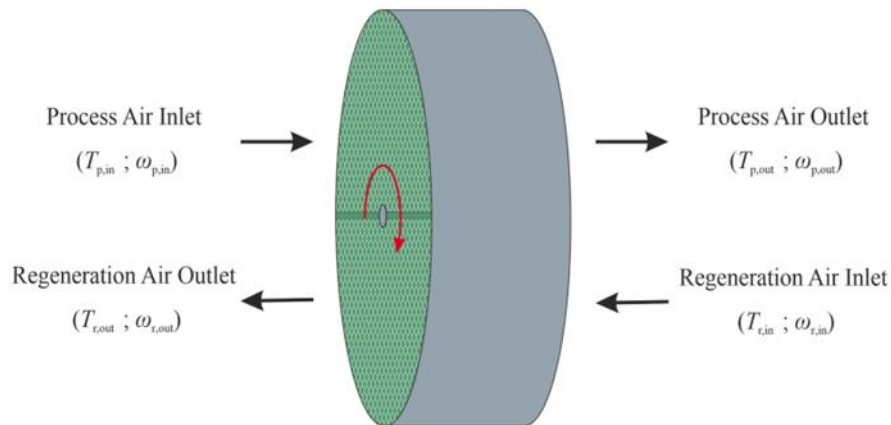


Figure 1.5. Representation of desiccant wheel (Güzelel et al., 2021).

In DAC systems, some type of evaporative cooler is typically used to reduce the temperature of the process air leaving the DW with reduced humidity ratio but increased temperature to the desired supply temperature (Goldsworthy and White, 2011).

Direct Evaporative Coolers (DEC) have only wet channels, as shown in Figure 1.6a. The working principle of a direct evaporative cooler involves spraying water into process air to achieve cooling. This process causes the water to evaporate by absorbing the heat energy from the hot air. As a result, both heat transfer and mass transfer occur in the process air, leading to a decrease in the temperature and an increase in its humidity ratio (Rafique et al., 2015).

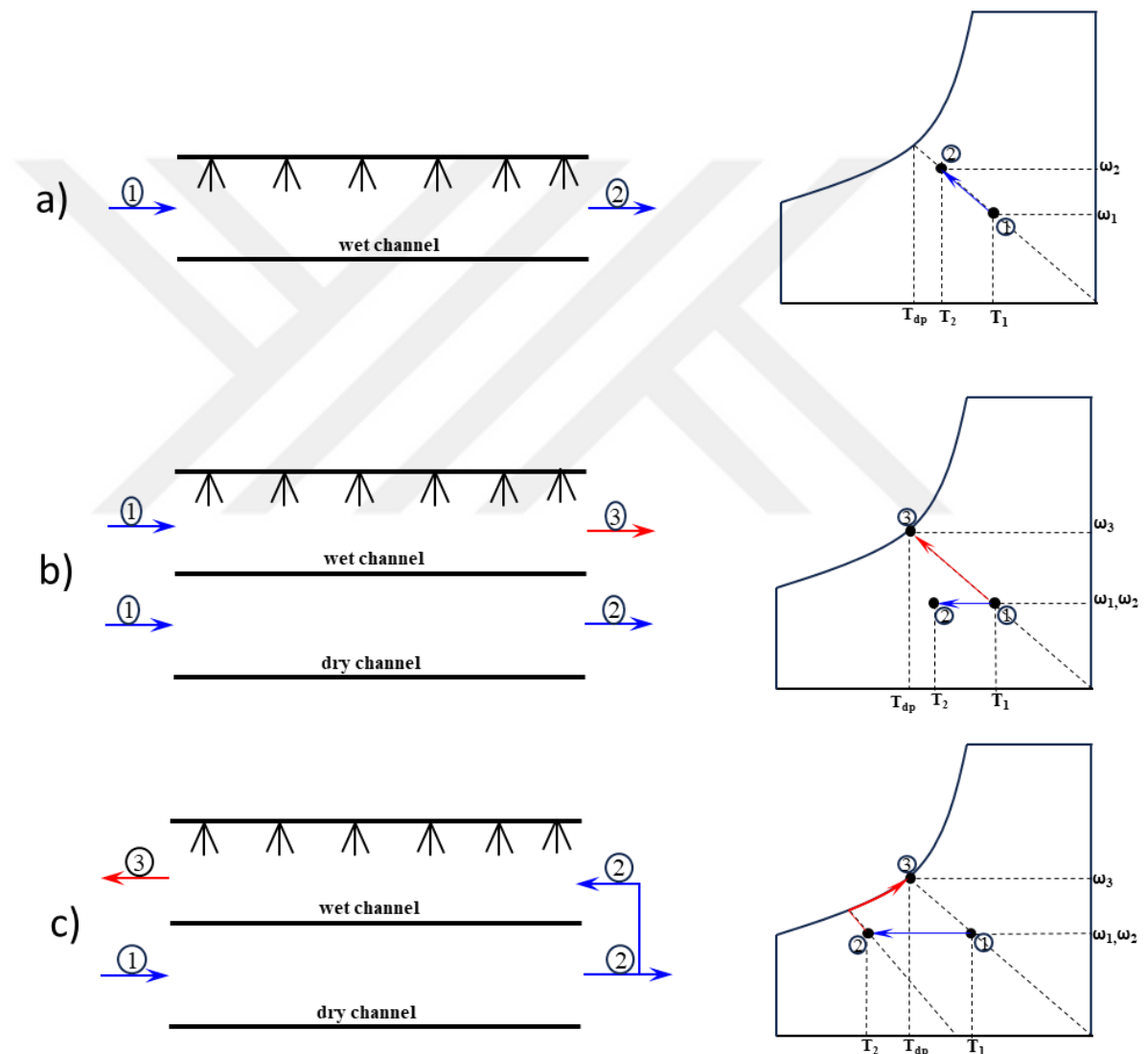


Figure 1.6. Schematic and psychrometric chart of evaporative coolers: (a) direct evaporative cooler, (b) indirect evaporative cooler, and (c) dew-point indirect evaporative cooler used in desiccant air-conditioning systems.

Unlike the DEC devices, indirect evaporative coolers (IDEC) have two channels: one wet and one dry, as seen in Figure 1.6b. The same process occurs in the wet channel of IDEC devices as in the wet channel of DEC devices. However, in IDEC devices, the temperature of the process air decreases while its humidity ratio remains constant. This characteristic eliminates the need for additional dehumidification (Rafique et al., 2015).

Compared to other evaporative coolers, a dew-point indirect evaporative cooler (DPIEC) can cool process air to the dew-point temperature. Unlike IDEC devices, DPIEC devices transfer a portion of the process air to the wet channel to achieve dew-point cooling, as shown in Figure 1.6c. Additionally, the DPIEC device maintains the humidity ratio of the process air constant (Zhu et al., 2022).

In the regeneration section of the desiccant wheel, the regeneration air must be hotter than the process air to enhance its dehumidifying capability. Therefore, a heat source is required to increase the temperature of the regeneration air. Electric heaters, waste heat, and solar energy are examples of heat sources used in a desiccant system. Electric heaters are mostly used as auxiliary heat sources, while waste heat and solar energy primarily supply the necessary heat to achieve the optimum regeneration temperature. When waste heat and solar energy cannot provide the required heat, an auxiliary heat source is engaged to supply the additional heat needed (Rambhad et al., 2016).

Heat exchangers are often used for heat recovery in DAC systems. In air-conditioning, clean and fresh air is needed to supply the conditioned space. The indoor air, which is more polluted than fresh air but cooler than outdoor air, undergoes heat recovery with heat exchangers instead of being discharged directly to the outside environment. This process reduces the cooling load of the system, thereby increasing its efficiency (Daou et al., 2006).

1.4. Classification of Desiccant Materials

The performance of the desiccant wheel is significantly influenced by the material it is made from, as well as the operating conditions. Therefore, having a high adsorption capacity and good regeneration ability in the desiccant material is vital. A high adsorption capacity enables the material to absorb more moisture, while a good regeneration ability allows it to be regenerated at lower temperatures, reducing the need for extensive cooling of the process air (Zheng et al., 2014). Various dehumidifying materials have been extensively explored in the literature. Zheng et al. (2014) classified these materials into three primary categories: composite, nanoporous, and polymeric. The materials examined in their study are listed in Figure 1.7. Among them, LT3, a molecular sieve was categorized as a nanoporous inorganic material, with pore size being a key reference in this classification. Additionally, the adsorption isotherms of various desiccant materials were also shared in the same study (Figure 1.8).

A comprehensive literature review revealed the adsorption capacity and regeneration abilities of different materials. As seen in Figure 1.8, zeolite exhibits a greater moisture retention capacity than traditional silica gel at low relative humidity.

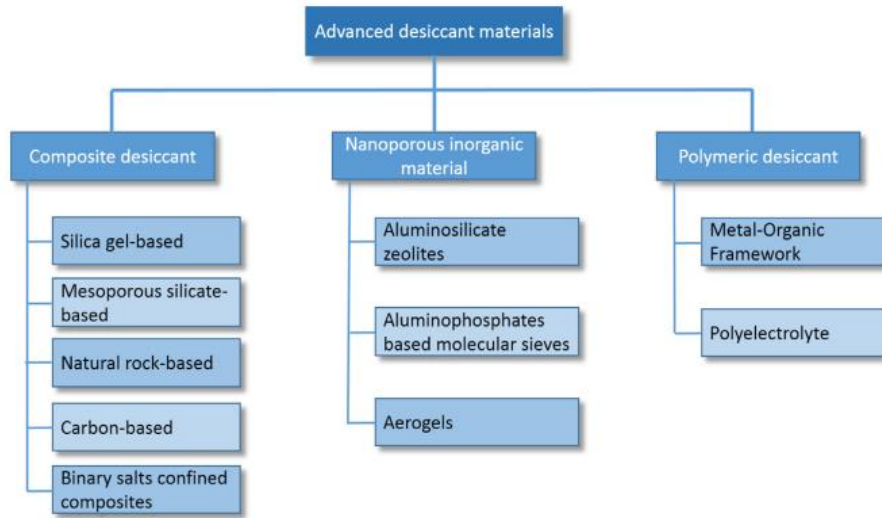


Figure 1.7. Classification of desiccant materials (Zheng et al., 2014).

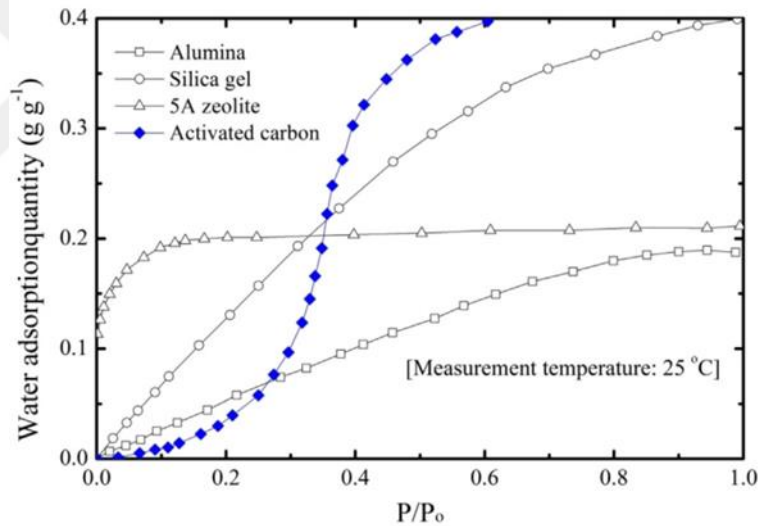


Figure 1.8. Adsorption curves of different materials at 25 °C (Zheng et al., 2014).

Shehadi (2018) conducted an examination of DAC systems for building air-conditioning. The study encompassed various DAC systems, desiccant materials, and associated techniques. Desiccant materials were categorized into solid and liquid forms, as illustrated in Figure 1.9. The study compared both solid and liquid dehumidifiers. The findings indicated that liquid desiccant materials are more effective at retaining moisture and can regenerate at lower temperatures compared to their solid counterparts.

According to a literature review conducted by Misha et al. (2012) solid desiccant materials are more commonly used in dehumidification applications. This preference is due to their ease of installation, lack of harmful effects, and minimal maintenance requirements. However, liquid

desiccant materials have a higher moisture removal capacity at lower regeneration temperatures compared to solid desiccant materials. In a study by Sahlot and Riffat (2016), it was noted that liquid desiccant materials, such as lithium chloride, lithium bromide, and other salt-based corrosives, can damage desiccant systems due to their corrosive nature. Additionally, a significant disadvantage of liquid desiccant materials is their potential to mix with the air they dehumidify, posing health risks to humans. Moreover, operating large quantities of liquid desiccants requires high pump power, leading to increased energy costs.

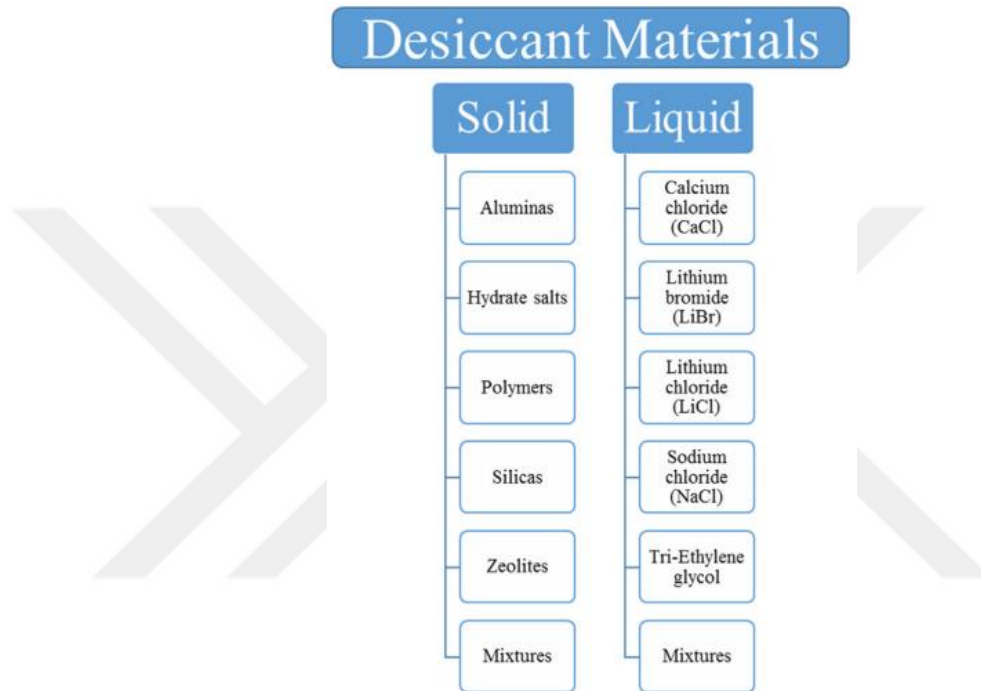


Figure 1.9. Classification of desiccant materials (Shehadi, 2018).

The aim of this study is to accurately model the LT3 (molecular sieve) desiccant wheel, which can be used in various climates and operational areas, under different input conditions. Various modeling tools were employed to simulate the desiccant wheel. The developed models were compared based on the determined performance parameters and the most effective and practical models were identified. The most effective and practical models will be shared for researchers' use.

2. PRELIMINARY WORK

The literature review commenced by examining studies focusing on traditional silica gel alongside various other desiccant materials. These investigations aimed to identify key input parameters that influence output conditions. Additionally, the review encompassed different modeling approaches applied to desiccant wheels. Finally, specific research was conducted on desiccant wheels fabricated from LT3, a molecular sieve.

2.1. Studies on Desiccant Wheels Manufactured from Various Materials

Intini et al. (2015) examined the AQSOA zeolite-based desiccant wheel both experimentally and numerically. They developed a gas-solid side numerical model and calibrated it with experimental data, although the model itself was not shared. Using this model, they investigated the effects of area ratio, process inlet temperature, and humidity ratio, as well as face velocity parameters on performance. Their findings concluded that, under conditions of constant inlet velocity and constant regeneration temperature, the moisture removal capacity increases proportionally with the humidity ratio drop. The maximum moisture removal capacity was achieved at the highest humidity ratio drop value, which occurred in the low to medium temperature range with an area ratio of 0.5. They also concluded that the area ratio significantly impacts the optimal rotation speed. The study found that the inlet humidity ratio had a greater effect on moisture removal efficiency than the inlet temperature. Furthermore, dimensionless analysis proved useful in determining the optimal rotation speed as a function of the inlet surface speed.

Chen et al. (2016) examined the transient adsorption rates of composite desiccant materials and conventional desiccant materials mixed at different percentages, as shown in Figure 2.1. They produced a composite desiccant wheel using silica gel, polyacrylic acid, activated alumina, molecular sieve, and diatomite. The desiccant wheel comprised 80% silica gel, 10% polyacrylic acid, and 10% polyacrylic sodium (SG8PS1PA1) due to its high adsorption rate at high relative humidity. The composite desiccant wheel then was integrated into a DAC system with a heat pump. The study observed the effects of the evaporator and condenser in different system locations under both summer and winter conditions. The results indicated that dehumidification performance improves by first condensing moisture in the evaporator and then using the desiccant wheel for a second dehumidification process.

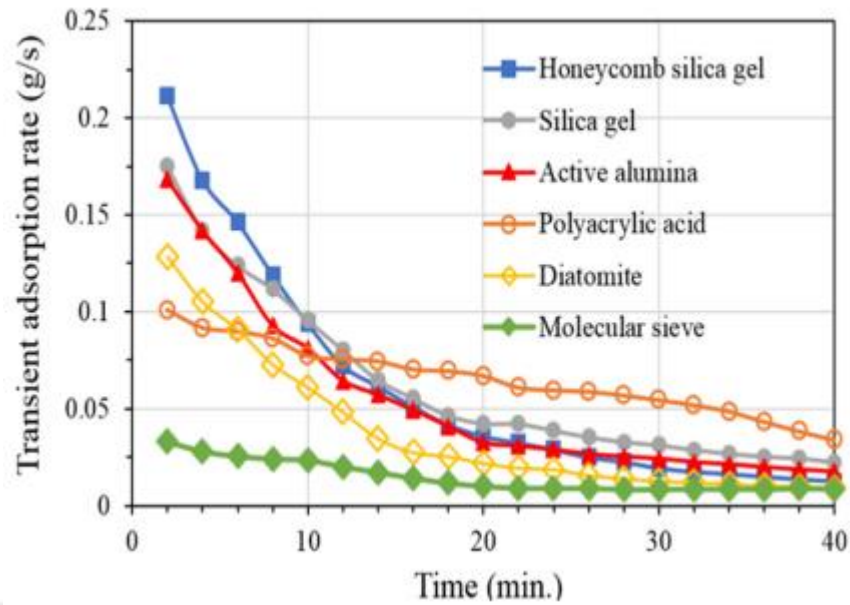


Figure 2.1. Transient adsorption rate of different desiccant materials (Chen et al., 2016).

Jia et al. (2006) parametrically examined the composite and silica gel desiccant wheels they produced using experimental data. The composite desiccant wheel was made from a combination of LiCl and silica gel. The phenomenon of lyolysis, which involves the formation of acids and bases due to the interaction of salt and a solvent, is prevented by the composite made of silica gel and LiCl. They examined the effects of parameters such as inlet relative humidity, inlet process air temperature, regeneration temperature, and airflow rate on performance parameters. The results indicated that the dehumidification capacity of the new composite desiccant wheel is 50% greater than that of the traditional silica gel desiccant wheel. It was observed that the incorporation of LiCl into the silica gel increased the moisture adsorption capacity of the wheel. High regeneration temperatures provided a high dehumidification capacity for both types of wheels, but the optimal regeneration temperature differed for each. The optimal regeneration temperature for the composite desiccant wheel was lower than that for the silica gel desiccant wheel.

Al-Alili et al. (2015) examined a desiccant rotor made of a functional adsorbent material called zeolite 01 (FAM-Z01) in an experimental setup. The study investigated the effects of parameters such as the humidity ratio and temperature of the process air, the temperature of the regeneration air, the ventilation mass flow rate, and the rotational speed of the desiccant wheel on performance. The results showed that as the ambient temperature decreased, the latent coefficient of performance (COP_{lat}) and moisture removal capacity (MRC) increased. High humidity levels also increased both COP_{lat} and MRC. While an increase in ventilation mass flow rate increased MRC, the COP_{lat} remained approximately the same. High regeneration temperatures reduced the process air outlet humidity ratio, but the energy required for dehumidification resulted in a decrease in the COP_{lat} .

Ge et al. (2010) developed a numerical model for a haloid compound desiccant wheel, considering both solid-side and gas-side resistances. However, the model that included only gas-side resistance was more consistent with the experimental results. The study found that the compound desiccant wheel performed better in climates with moderate temperatures or high humidity. Using the calibrated model, the desiccant wheel was examined parametrically under different operating conditions. For simulated operating conditions, an angle of 100-160 degrees is recommended for the regeneration section. In high humidity conditions, the compound desiccant wheel achieved higher moisture removal and a better desiccant coefficient of performance (DCOP). However, in low humidity conditions, to trade-off dehumidification or DCOP, the process air velocity should be between 2 m/s and 3.5 m/s with a regeneration air temperature of 80-95°C and a regeneration air velocity of 2.5-3.5 m/s. The ideal rotation speed for baseline values is 12 RPH. The ideal rotation speed is directly proportional to the regeneration angle, ambient temperature, ambient humidity ratio, regeneration air velocity, and regeneration air temperature, but inversely proportional to the humidity ratio of the regeneration air.

White et al. (2011) experimentally investigated desiccant wheels made of silica gel, ferroaluminophosphate (FAM-Z01) zeolite material, and superadsorbent polymer. The silica gel desiccant wheel was chosen as the reference material due to its extensive analysis in the literature. For all wheels, the regeneration and process areas were set to 50%-50%. Experiments were conducted across a wide relative humidity range (20-90%). For all experimental conditions, the process air inlet humidity ratio and the regeneration air inlet humidity ratio were kept the same. The optimal rotation speed was set at 20 RPH and maintained constant under all test conditions. The test results indicated that the superadsorbent polymer desiccant wheel absorbed more moisture than the silica gel desiccant wheel at low regeneration temperatures. Zeolite desiccant wheels were generally less efficient in absorbing moisture.

Cao et al. (2014) investigated the effect of various input parameters, such as process air inlet temperature and humidity ratio, regeneration air inlet temperature, and rotation speed of a new polymer desiccant wheel, as well as geometric input parameters like desiccant wheel thickness and diameter, on performance parameters. The performance parameters defined were Moisture Removal Capacity (MRC), Coefficient of Performance latent (COP_{lat}), and Sensible Energy Ratio (SER). The experimental studies concluded that the new polymer desiccant material can be regenerated at low temperatures, such as 50 °C. However, high process inlet temperature caused a decrease in the MRC. While high humidity ratio increased the MRC and COP_{lat} parameters, it had negative effects on the SER parameter. Conversely, high regeneration temperatures produced favorable results for the MRC parameter but led to a decrease in the COP_{lat} parameter. In the studies with four wheels of different thicknesses, the MRC and COP_{lat} parameters reached high values at low rotation speeds and with thicker wheels. The results indicated that the desiccant wheel achieved maximum MRC and COP_{lat} values under different conditions, suggesting that the balance between MRC and COP_{lat} should be

considered according to the operating conditions of the desiccant wheel. It was also observed that the SER increased linearly with both rotation speed and wheel thickness.

Zhang et al. (2005) experimentally examined new silica gel-calcium chloride composite wheels. They measured the adsorption curves of these different composite materials at various relative humidity levels and observed that the adsorption curves of the composite desiccant materials varied depending on the mixing ratios of the materials. The study concluded that composite desiccant materials are suitable for improving the performance of desiccant wheels. The researchers investigated input parameters such as dehumidifier mass, regeneration temperature, regeneration flow rate, rotation speed, and regeneration angle while keeping other input parameters constant. The composite desiccant wheels demonstrated better performance compared to silica gel and calcium chloride (CaCl_2) wheels. The parametric study revealed that the optimum operating range of the composite desiccant wheel varies according to the CaCl_2 ratio.

Jia et al. (2007) developed a mathematical model for desiccant wheels made of different materials, which was subsequently verified through experiments. Using the validated model, they examined the performance of the desiccant wheels under different operating conditions and compared them with the silica gel desiccant wheel. The study focused on the effects of various input parameters on the amount of dehumidification and the DCOP performance parameters. The DCOP defined in their study differs from that in the current literature. The input conditions considered included regeneration temperature, process air inlet temperature, relative humidity, and the thickness of the desiccant wheel. The results showed that the composite desiccant wheel was more hygroscopic than the silica gel wheel, making it easier to regenerate. The study concluded that the more compact and lower operating-cost composite material is more suitable for dehumidifying systems. Additionally, under certain operating conditions, the composite desiccant wheel absorbed 20-30% more moisture than the silica gel desiccant wheel.

Ge et al. (2008) experimentally examined composite desiccant wheels made of silica gel and lithium chloride in a two-stage dehumidification process. In the study, half of the wheel was reserved for Stage 1 dehumidification and the other half for Stage 2 dehumidification. For each half of the wheel, 45 degrees was allocated for regeneration air and the remaining 135 degrees for process air. The desiccant wheel was tested under different operating conditions in the experimental setup, with laminar flow maintained in the channels, unlike other studies. The study examined rotation speed, temperature, and thickness of the regeneration air using dehumidification and DCOP performance parameters under various climatic conditions. The results indicated that the 100 mm thick wheel performed better than the 70 mm and 40 mm thick wheels. It was demonstrated that a single wheel could be effectively used for a two-stage dehumidification process. The study concluded that using one wheel for a two-stage dehumidification process is suitable for reducing the size of two-stage and two-wheel dehumidification systems without any loss of performance.

Goldsworthy et al. (2015) tested the theory that moisture can be removed if the partial pressure of water vapor in the process air is greater than the partial vapor pressure of the regeneration air. The experimental setup used a desiccant wheel made of AQSOA-Z02 zeolite. The study examined parameters such as regeneration temperature, process air inlet temperature, and desiccant wheel rotation speed, focusing on performance parameters that consider both dehumidification and the thermal energy required to remove the moisture. Additionally, the study compared regeneration with steam to regeneration with air. The results confirmed that moisture can indeed be removed using steam. The study suggested that this system could be applied in industrial areas where superheated water steam is already in use and readily available.

Park et al. (2023) hypothesized that the dehumidification capacity of traditional desiccant materials was limited and recommended metal-organic framework (MOF) material as an alternative desiccant material. They manufactured desiccant wheels from this material and tested them under various operating conditions, comparing the results with desiccant wheels made of silica gel, zeolite, and silica gel composite materials reported in the literature. In the study, the area of the desiccant wheel was divided into 75% process air and 25% regeneration air. The effects of parameters such as process air inlet temperature, process air humidity ratio, regeneration air temperature, volumetric flow rate, and rotation speed on performance parameters such as SER, DCOP and MRC were examined. As a result of this comprehensive study, it was observed that the MOF desiccant wheel had 53% lower SER and 139% higher specific moisture removal capacity (SMRC) than the traditionally used silica gel desiccant wheel. A low SER is preferred in desiccant wheels because it indicates a lower cooling load, which in turn reduces the operating cost of DAC systems.

Kang and Lee (2017) conducted an experimental analysis of three different polymer desiccant wheels with varying thicknesses. The dehumidification effectiveness, thermal effectiveness values, and overall performance of the desiccant wheels were examined. The experiments showed that polymer desiccant wheels have higher dehumidification performance compared to other desiccant wheels and result in a lower sensible temperature increase in the outlet temperature of the process air.

Eicker et al. (2012) experimentally examined four different desiccant wheels made of titanium silicate, lithium chloride, silica gel, and a composite of silica gel and lithium chloride. The pore structure of three of the desiccant wheels was honeycomb, while the wheel made solely of lithium chloride had a sinusoidal pore structure. The wheels were tested using a parametric study with different input parameters, such as rotation speed, air humidity ratio, volumetric flow rates of regeneration air and process air, and regeneration temperature. The wheels were evaluated based on performance parameters, including dehumidification capacity, dehumidification efficiency, and regeneration-specific heat input. The study found that the optimum rotation speed for the silica gel desiccant wheel is higher than that for the lithium chloride desiccant wheel. Adding lithium chloride to silica gel increased the dehumidification capacity of the wheel by 3 g/kg and the dehumidification

efficiency by 90%. The best performance was achieved when the volume flow rate of both process and regeneration air was 75% of their maximum values. Although higher flow rates increased the enthalpy change, they did not lead to an increase in dehumidification capacity. Additionally, high regeneration temperatures allowed for more dehumidification but negatively affected energy efficiency and the exit temperature of the process air. The study also found that reducing the inlet humidity ratio of the regeneration air significantly improved dehumidification capacity. Specifically, reducing the inlet relative humidity of the regeneration air from 20% to 6% nearly doubled the dehumidification capacity.

Rambhad et al. (2020) examined and compared the performance of molecular sieve desiccant wheels and silica gel desiccant wheels using manufacturer data. The determined inlet conditions were simulated in the manufacturer's program, and the outlet conditions were obtained. The study considered two different ratios of process area to regeneration area: 1:1 and 3:1. Additionally, parameters such as regeneration air inlet temperature, rotation speed, and the mass flow rates of process and regeneration air were examined parametrically. The study found that the molecular sieve desiccant wheel showed the highest performance at 20 RPH, a regeneration temperature of 90 °C, and a 1:1 area ratio. Conversely, the silica gel desiccant wheel performed best at 20 RPH, a regeneration temperature of 90 °C, and a 3:1 area ratio.

2.2. Studies on Modelling Methods of Desiccant Wheel

Mathematical models for desiccant wheels allow for accurately predicting the outlet conditions of the process air corresponding to specified input conditions. This capability enables the optimization of the desiccant wheel for specific air-conditioning projects using the model. Additionally, integrating the model into various transient energy analysis software (such as TRNSYS and EES) significantly facilitates the hourly analysis of a general system. Furthermore, it greatly simplifies adjusting the necessary input parameters to achieve the specified operating conditions.

In the literature, models of varying complexity and accuracy have been developed using different modeling techniques to model desiccant wheels with various desiccant materials.

Parmar and Hindoliya (2011) modeled a silica gel desiccant wheel using various artificial neural network (ANN) algorithms. The study tested numerous training algorithms, including `trainrp`, `trainbfg`, `trainbr`, `traincgb`, `traincgf`, `traincgp`, `traingd`, `traingdm`, `traingda`, `traingdx`, `trainlm`, `trainoss`, `trainr`, `trainrp`, and `trainscg`. For each model, the number of hidden layers was set to 2, the number of neurons in each hidden layer was set to 10, and the `tansig` activation function was selected. The developed models were validated with experimental data. As a result, the `trainlm` algorithm provided the best performance among the models.

Çerçi and Hürdoğan (2020) developed models for a silica gel desiccant wheel using artificial neural networks and multiple linear regression (MLR) methods. The dataset required for the models was obtained from NovelAire software, which provided the outlet conditions of the desiccant wheel

under different inlet conditions. In the study, ANN models and MLR models were compared using performance parameters such as coefficient of determination (R^2), root mean square error (RMSE), and mean average error (MAE). For the ANN models, the number of hidden layers and the number of neurons in each layer were kept constant, and the trainlm algorithm was selected as the training algorithm. Different activation functions were used for each ANN model. The results showed that the ANN-V coded model, with the tansig-pureline activation function, provided the best performance among the ANN models. Among the developed MLR models, the MLR-VI model of the 4th degree produced the best results. In the comparison between ANN and MLR models, the ANN model was found to be superior.

Motaghian et al. (2021) developed a model using artificial neural networks to analyze the performance of a silica gel desiccant wheel. The dataset required for training the ANN model was generated from their developed transient coupled heat and mass transfer model, solved using a FORTRAN program. The model included numerous input parameters such as process air inlet temperature, humidity ratio, velocity, regeneration air inlet temperature, humidity ratio, velocity, desiccant wheel rotation speed, thickness, diameter, and purge angle. The resulting mathematical model was validated with experimental data. The study shared the training functions, the number of hidden layers, and the number of neurons used in the developed ANN models, and compared different ANN models. The model with 4 hidden layers and 50 neurons demonstrated the best performance.

Güzelel et al. (2021) modeled a silica gel desiccant wheel for balanced flow conditions. In their study, they obtained a comprehensive dataset from various studies in the literature for the silica gel desiccant wheel. The models developed with this dataset were tested individually for each dataset. Among the MLR models, the best result was given by the MLR-IV model, while among the MLPR models, the best result was obtained from the MLPR-III model. For the decision tree models, the best result was achieved by the DT-VII model. The RMSE and R^2 values of these models are shown in Table 2.1. According to this table, the best model is the DT-VII model.

Table 2.1. Comparison of regression models (Güzelel et al., 2021).

Model	Temperature		Humidity ratio	
	R^2	RMSE [°C]	R^2	RMSE [g/kg]
MLR-IV	0.9894	0.8743	0.9912	0.3701
MLP-III	0.9817	1.1526	0.9885	0.4227
DT-VII	0.9986	0.3295	0.9994	0.0995

Güzelel et al. (2022) extended their study on silica gel desiccant wheel for balanced flow (Güzelel et al., 2021) to include unbalanced flow conditions. They developed MLR and ANN models to predict the output conditions of a silica gel desiccant wheel for unbalanced flow conditions. They

gathered datasets from various studies through a comprehensive literature review to obtain a wide range of input and output conditions for the silica gel desiccant wheel. The selected input parameters included the regeneration area to process area ratio, process air inlet velocity, regeneration air inlet velocity, desiccant wheel rotation speed, process air inlet temperature and humidity ratio, and regeneration air inlet temperature and humidity ratio. A main dataset was constructed using various input and output conditions gathered from different studies, which was then used for the development of MLR and ANN models. The performance parameters and the number of parameters included in the developed MLR models were considered for performance and ease of use. Both the ANN and MLR models were compared using R^2 and RMSE performance parameters. The study found that among the MLR models, the response surface model provided the best results. Additionally, all the developed decision tree models outperformed all the MLR models. Among the ANN models, the M^{PUK} model provided the best results, despite not being previously used for modeling in the literature.

2.3. Studies on LT3 Desiccant Wheels

In the literature, there are a limited number of studies on molecular sieve desiccant wheels, including those on the commercially known LT3 molecular sieve desiccant wheel.

Zendehboudi (2016) developed a hybrid model composed of a least squares support vector machine and a genetic algorithm to predict the output conditions of LT3 and silica gel desiccant wheels. The performance of the developed model was evaluated using performance parameters such as the coefficient of determination, mean average error, and mean squared error. Through these performance parameters, the predicted values were compared with the actual values of parameters defining the performance of the desiccant wheel under different inlet conditions, including dehumidification effectiveness, sensible energy ratio, process outlet temperature, and process outlet moisture. The performance values of the model obtained in this study are as follows: a mean average error of less than 0.23, a coefficient of determination greater than 0.994, and a mean squared error of less than 0.072.

Zendehboudi and Li (2018) used a two-step optimization method consisting of response surface methodology and multi-objective optimization to optimize the operating conditions of desiccant wheels made from molecular sieve and silica gel. The response surface methodology was employed to predict the outlet conditions of the desiccant wheels, yielding a coefficient of determination value of 0.95. This model was then combined with the multi-objective optimization method to determine the optimal operating values of the desiccant wheel. In the study, equations providing the process air outlet humidity ratio and temperature for both molecular sieve and silica gel desiccant wheels were shared. However, these models did not include the process air inlet temperature and the velocities of the process and regeneration air. The study presented optimization contours for the process area/regeneration area ratios, the rotational speed of the wheel, the diameter of the wheel, and the regeneration air inlet temperature.

Alahmer et al. (2019) developed a mathematical model to observe the effects of certain input parameters on the performance of silica gel desiccant wheels and LT3 desiccant wheels. The developed model was validated using experimental data from the literature. With this model, the effects of parameters such as the inlet humidity ratio of the process air, the inlet volume flow rate of the process air, the ratio of regeneration air to process air, the inlet temperature of the regeneration air, and the rotational speed of the desiccant wheel on the dehumidification performance were examined. Additionally, the wheels were compared at different regeneration area/process area ratios. The study concluded the following: an increase in regeneration temperature from 70°C to 140°C resulted in an increase of 2.065 g/kg in the dehumidification capacity of the silica gel desiccant wheel, while the LT3 desiccant wheel's dehumidification capacity increased by 5.71 g/kg under the same condition. The optimal rotational speed was found to be 14 RPH. Furthermore, the desiccant wheel absorbed more moisture at lower speeds of the process air.

In the comprehensive literature review conducted (Section 2), although some studies have addressed the dehumidification performance of the LT3 desiccant wheel, no mathematical model has been found that predicts the output conditions for specific input parameters of the LT3 desiccant wheel. In this context, the aim of this study is to accurately model the LT3 (molecular sieve) desiccant wheel, which can be used in various climates and operational areas, under different input conditions. Various modeling tools have been employed to simulate the desiccant wheel. This study aims to compare these models based on determined performance parameters and present the most effective and practical models to the literature.



3. MATERIAL AND METHOD

In this thesis, numerical models were developed to determine the conditions of the process air exiting the desiccant wheel using LT3 desiccant material. The necessary data for developing these models were obtained from software provided by a company (Novelair) that produces silica gel and LT3 desiccant wheels.

Numerous operational parameters affect the dehumidification performance of a desiccant wheel. Based on the literature review, the following parameters were used as inputs for the developed models:

- Process air inlet temperature ($T_{p,in}$)
- Process air inlet humidity ratio ($\omega_{p,in}$)
- Regeneration air inlet temperature ($T_{r,in}$)
- Regeneration air inlet humidity ratio ($\omega_{r,in}$)
- Process air velocity ($V_{p,in}$)
- Regeneration air velocity ($V_{r,in}$)
- Rotational speed (N)

The developed models directly predict the outlet temperature and humidity ratio of the process air:

$$T_{p,out} = f(T_{p,in}, \omega_{p,in}, T_{r,in}, \omega_{r,in}, N, V_{p,in}, V_{r,in}) \quad (1)$$

$$\omega_{p,out} = f(T_{p,in}, \omega_{p,in}, T_{r,in}, \omega_{r,in}, N, V_{p,in}, V_{r,in}) \quad (2)$$

Conditions of the regeneration air can be obtained by writing mass and energy balance equations for the desiccant wheel.

Table 3.1. Range of model input parameters.

Input	Range		Output	No of Data
$T_{p,in}$	24-40	[°C]	$T_{p, out}$ $\omega_{p, out}$	32,975
$\omega_{p,in}$	6-18	[g/kg]		
$T_{r,in}$	66-90	[°C]		
$\omega_{r, in}$	6-18	[g/kg]		
N	6-42	[rev/h]		
V_p	1.57-3.88	[m/s]		
V_r	0.39-5.88	[m/s]		

Using the software provided by the manufacturer, the humidity ratio and temperature of the process air exiting the desiccant wheel were obtained for 32,975 different input conditions. The range of input parameters used is shown in Table 3.1.

Within the scope of the study, regression models were developed in two main categories: Multiple Linear Regression (MLR) and Machine Learning (ML). Machine learning algorithms for regression can be further classified into Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Decision Tree (DT).

3.1. Multiple Linear Regression Models (MLR)

Multiple linear regression (MLR) models were developed using JMP software (Figure 3.1), a robust statistical analysis program that offers a range of features, including the design of experiments, the creation of statistical models, and versatile data visualization capabilities. As depicted in Figure 3.1, the data table within the JMP program serves as the foundational dataset for model development. Utilizing the interface illustrated in Figure 3.2, seven regression models were constructed. These models encompass 1st Degree, 1st Degree cross, 2nd Degree, 2nd Degree cross, 3rd Degree, 3rd Degree cross, and Response Surface models.

The equations (Equation 3 to 9) of these MLR models, in their general form, incorporate several terms: y denotes the dependent variable, x signifies the independent variables, p represents the number of independent variables, and β corresponds to the coefficients. The comprehensive representation of these MLR models is illustrated in the accompanying equations, reflecting the complexity and interactions between the variables (Montgomery and Runger, 2020).

The first MLR model is a 1st Degree model, which can be expressed in the following general form:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i \quad (3)$$

where y is either $T_{p,out}$ or $\omega_{p,out}$.

The second MLR model is a 1st Degree model with cross terms:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ij} x_i x_j \quad (4)$$

The third MLR model is a 2nd Degree model:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^p \beta_{ii} x_i^2 \quad (5)$$

The fourth MLR model is a 2nd Degree model with cross terms:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^p \beta_{ii} x_i^2 + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ij} x_i x_j + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{iij} x_i^2 x_j + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ijj} x_i x_j^2 \quad (6)$$

The fifth MLR model is a Response Surface model:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^p \beta_{ii} x_i^2 + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ij} x_i x_j \quad (7)$$

The sixth MLR model is a 3rd Degree model:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^p \beta_{ii} x_i^2 + \sum_{i=1}^p \beta_{iii} x_i^3 \quad (8)$$

The last MLR model is a 3rd Degree model with cross terms:

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \sum_{i=1}^p \beta_{ii} x_i^2 + \sum_{i=1}^p \beta_{iii} x_i^3 + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ij} x_i x_j + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{iij} x_i^2 x_j + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ijj} x_i x_j^2 + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{iiij} x_i^3 x_j + \sum_{i=1}^{p-1} \sum_{j=i+1}^p \beta_{ijjj} x_i x_j^3 \quad (9)$$

	Tp.in	Wp.in	Tr.in	Wr.in	N	Vp	Vr	Tp.out	Wp.out
1	28	9	70	9	36	3.15	2.36	46.7	5.35
2	28	9	70	9	36	3.88	4.85	47	4.94
3	28	9	70	9	36	3.15	3.93	48.6	4.85
4	28	9	70	9	36	2.44	3.04	50.6	4.84
5	28	9	70	9	36	3.88	5.88	47.4	4.82
6	28	9	70	9	36	3.15	4.72	49	4.72
7	28	9	70	9	36	2.44	3.65	51	4.72
8	28	9	70	9	42	3.88	0.97	37.2	7.71
9	28	9	70	9	42	3.88	1.94	43.1	6.2
10	28	9	70	9	42	3.88	2.91	45.7	5.54
11	28	9	70	9	42	3.88	4.85	47.4	5.06
12	28	9	70	9	42	3.15	3.93	49.1	5
13	28	9	70	9	42	3.88	5.88	47.8	4.93
14	28	9	70	9	42	3.15	4.72	49.6	4.87
15	28	9	74	9	6	3.88	0.97	35.8	7.14
16	28	9	74	9	6	3.15	0.79	36.4	7.03
17	28	9	74	9	6	2.44	0.61	37.1	6.94
18	28	9	74	9	6	3.88	1.94	39	6.24
19	28	9	74	9	6	3.15	1.57	40.3	5.94
20	28	9	74	9	6	2.44	1.22	42	5.59
21	28	9	74	9	6	1.57	0.79	44.8	5.11
22	28	9	74	9	6	3.88	2.91	40.7	5.77
23	28	9	74	9	6	3.15	2.36	42.6	5.32
24	28	9	74	9	6	2.44	1.83	44.7	4.86
25	28	9	74	9	6	1.57	1.18	47.6	4.32
26	28	9	74	9	6	3.88	4.85	41.9	5.47
27	28	9	74	9	6	3.15	3.93	44.4	4.83
28	28	9	74	9	6	2.44	3.04	47	4.25
29	28	9	74	9	6	3.15	4.72	44.7	4.76
30	28	9	74	9	6	2.44	3.65	47.4	4.14
31	28	9	74	9	6	1.57	2.36	50.7	3.57
32	28	9	74	9	12	3.88	0.97	37	6.95
33	28	9	74	9	12	3.15	0.79	37.3	6.97
34	28	9	74	9	12	3.88	1.94	41.7	5.62
35	28	9	74	9	12	3.15	1.57	42.9	5.39

Figure 3.1. View of data table in JMP.

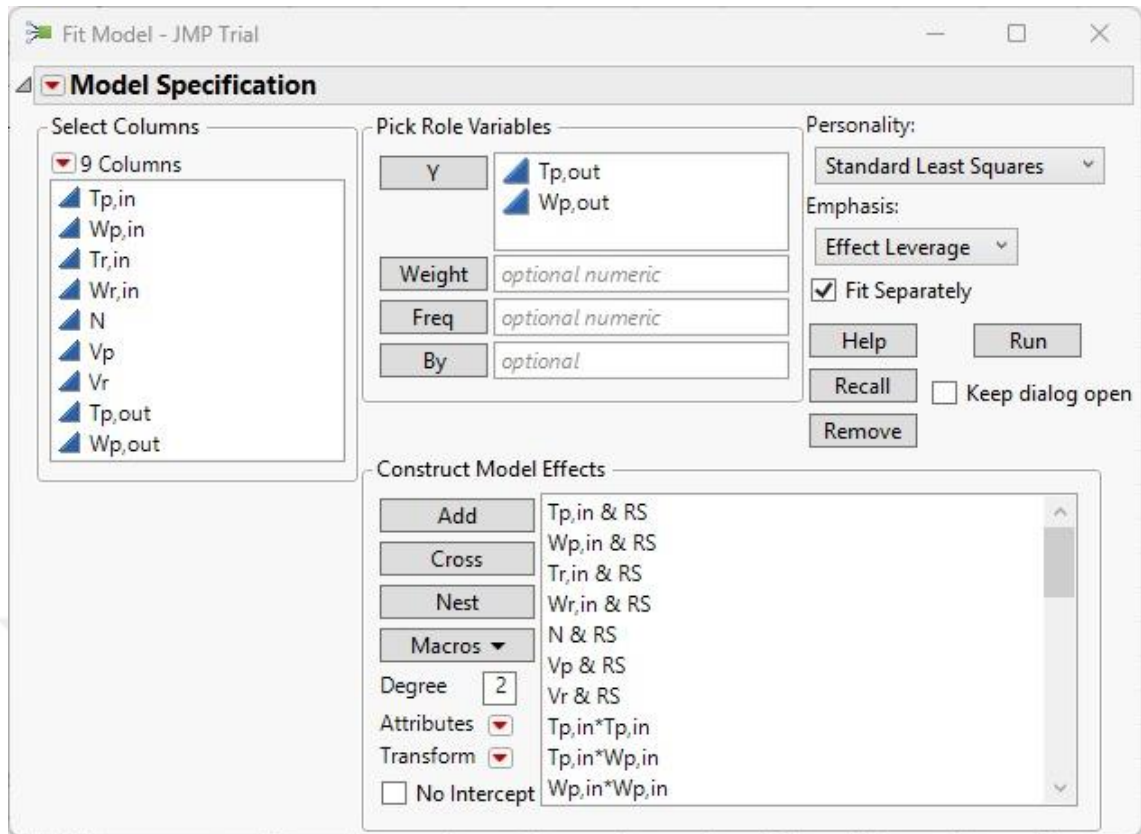


Figure 3.2. Developing Multiple Linear Regression models: image from the JMP software interface.

3.2. Machine Learning Models

The Machine Learning (ML) models for predicting the outlet conditions of process air were developed using the algorithms available in MATLAB software (The MathWorks). MATLAB is a high-level programming platform widely used for numerical computation, visualization, and programming. It provides a flexible environment for iterative analysis and design processes. Three different ML algorithms, namely decision tree, support vector machine, and multilayer perceptron, were employed in this study.

3.2.1. Decision Tree Models

Decision tree models are a type of machine learning algorithm used for both classification and regression tasks. The working principle of the decision tree is as follows: The model creates decision nodes based on the features in the data set, and branches emerge from these nodes. Each branch divides the data into subgroups based on the value of a particular attribute. Leaves are located at the ends of the branches. Leaves represent the results. There is no branching in leaf nodes, meaning these nodes indicate which class the data point belongs to or what value it carries (Pekel, 2020).

The example shown in Figure 3.3 is a random decision tree. The node at the top of the tree is called the root node. This node usually starts with the feature that provides the best discrimination. The nodes below it, are called internal nodes. Internal nodes divide the data into further subsets based on specified properties. The nodes at the end are called leaf nodes. Leaf nodes are located at the end

of the tree and provide the output value obtained from the regression of the given data in the previous branches. Parameters such as maximum branching, maximum leaf size, and pruning in decision trees developed in MATLAB affect the performance of the trees.

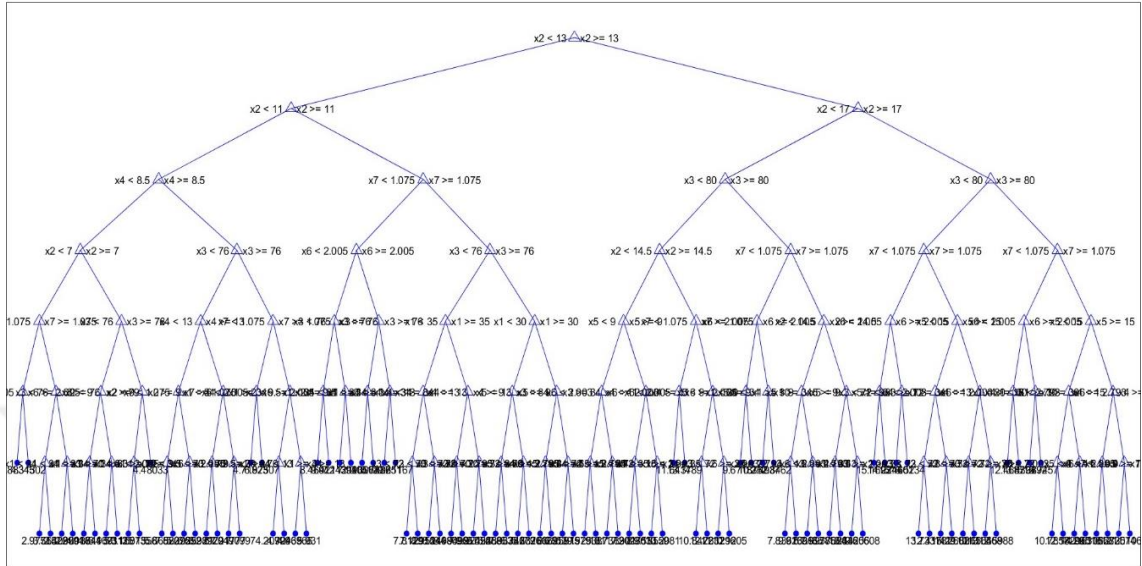


Figure 3.3. Decision tree example generated in MATLAB.

As seen in Table 3.2, a total of 45 decision trees were developed under three primary categories: random tree, adaptive boosting, and random forest models. The maximum number of trees was set to 500 and 1000 for the random forest and adaptive boosting methods. The minimum leaf size for all trees was fixed at 1. Additionally, three different predictors were evaluated: allsplits, curvature, and interaction curvature.

Table 3.2. Input parameters of Decision Tree models.

Model	Decision Tree	Max. Tree	Max. Split	Min. Leaf Size	Predictor
DT-1	Random Forest	500	500	1	allsplits
DT-2	Random Forest	500	500	1	curvature
DT-3	Random Forest	500	500	1	interaction-curvature
DT-4	Random Forest	500	600	1	allsplits
DT-5	Random Forest	500	600	1	curvature
DT-6	Random Forest	500	600	1	interaction-curvature
DT-7	Random Forest	500	700	1	allsplits
DT-8	Random Forest	500	700	1	curvature
DT-9	Random Forest	500	700	1	interaction-curvature
DT-10	Random Forest	1000	500	1	allsplits
DT-11	Random Forest	1000	500	1	curvature
DT-12	Random Forest	1000	500	1	interaction-curvature
DT-13	Random Forest	1000	600	1	allsplits
DT-14	Random Forest	1000	600	1	curvature
DT-15	Random Forest	1000	600	1	interaction-curvature
DT-16	Random Forest	1000	700	1	allsplits
DT-17	Random Forest	1000	700	1	curvature
DT-18	Random Forest	1000	700	1	interaction-curvature
DT-19	Adaptive Boosting	500	500	1	allsplits
DT-20	Adaptive Boosting	500	500	1	curvature
DT-21	Adaptive Boosting	500	500	1	interaction-curvature
DT-22	Adaptive Boosting	500	600	1	allsplits
DT-23	Adaptive Boosting	500	600	1	curvature
DT-24	Adaptive Boosting	500	600	1	interaction-curvature
DT-25	Adaptive Boosting	500	700	1	allsplits
DT-26	Adaptive Boosting	500	700	1	curvature
DT-27	Adaptive Boosting	500	700	1	interaction-curvature
DT-28	Adaptive Boosting	1000	500	1	allsplits
DT-29	Adaptive Boosting	1000	500	1	curvature
DT-30	Adaptive Boosting	1000	500	1	interaction-curvature
DT-31	Adaptive Boosting	1000	600	1	allsplits
DT-32	Adaptive Boosting	1000	600	1	curvature
DT-33	Adaptive Boosting	1000	600	1	interaction-curvature
DT-34	Adaptive Boosting	1000	700	1	allsplits
DT-35	Adaptive Boosting	1000	700	1	curvature
DT-36	Adaptive Boosting	1000	700	1	interaction-curvature
DT-37	Random Tree	1	500	1	allsplits
DT-38	Random Tree	1	500	1	curvature
DT-39	Random Tree	1	500	1	interaction-curvature
DT-40	Random Tree	1	600	1	allsplits
DT-41	Random Tree	1	600	1	curvature
DT-42	Random Tree	1	600	1	interaction-curvature
DT-43	Random Tree	1	700	1	allsplits
DT-44	Random Tree	1	700	1	curvature
DT-45	Random Tree	1	700	1	interaction-curvature

3.2.2. Support Vector Machine Models

The Support Vector Machine (SVM) modeling method is based on obtaining an optimal hyperplane to classify data or perform regression (Ergun et al., 2010). As seen in Figure 3.4 the goal of support vector regression is to find a hyperplane that best fits the data by using support vectors, minimizing the distance to all data points. The data points closest to this resulting line or plane are called support vectors. Support vectors are critical points that determine the position and orientation of the hyperplane (Ergun et al., 2010).

The kernel function is one of the key parameters in the operation of SVM. In MATLAB, several types of kernel functions are available, including linear, Gaussian, polynomial, and sigmoid. The solver is another essential parameter for SVM. In MATLAB, two solvers are available: sequential minimal optimization (SMO) and iterative single data algorithm (ISDA).

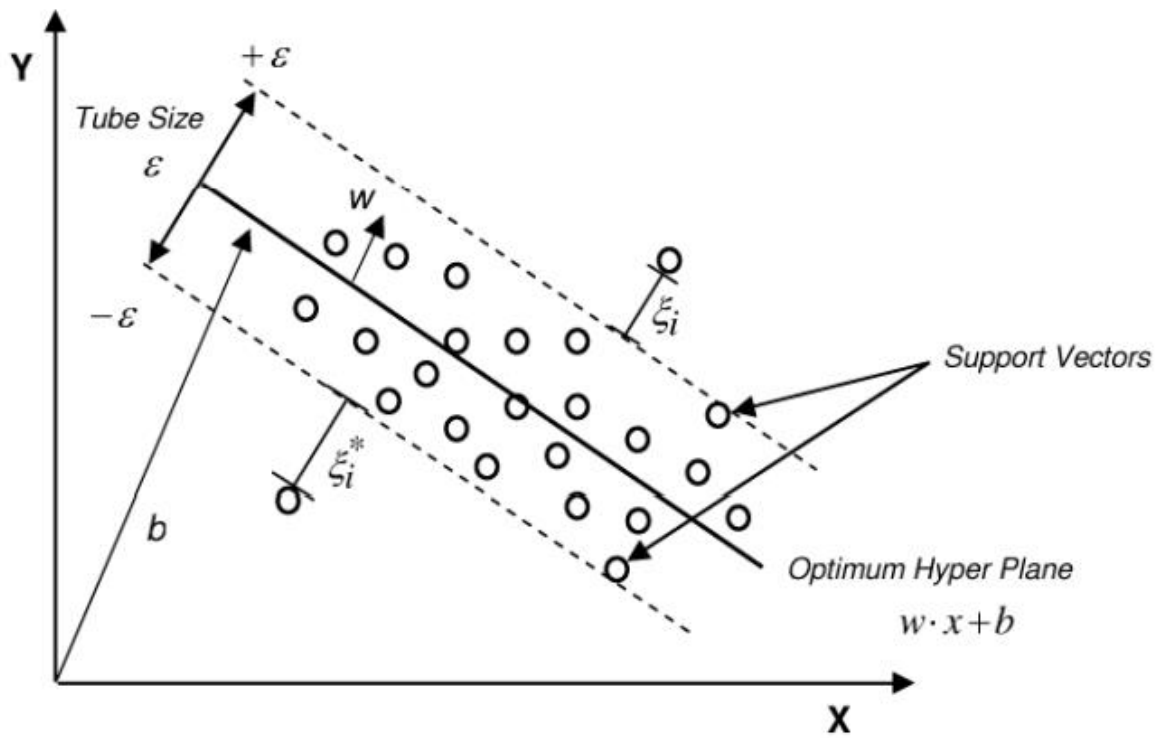


Figure 3.4. Support vector machine regression (Ergun et al., 2010).

In this study, 12 SVM models were obtained by varying the input parameters of the kernel function and solver, as shown in Table 3.3. The SMO and ISDA solvers available in MATLAB were tested for each kernel function. Additionally, for the Polynomial Kernel function, one of the available kernel functions in MATLAB, the degree of the polynomial was varied as 1, 2, and 3.

Table 3.3. Input parameters of Support Vector Machine models.

Model	Kernel Function	Degree of Polynom	Box Constrain	Kernel Scale	Solver
SVM-1	Linear	-	5	Auto	SMO
SVM-2	Linear	-	5	Auto	ISDA
SVM-3	Gaussian	-	5	Auto	SMO
SVM-4	Gaussian	-	5	Auto	ISDA
SVM-5	rbf	-	5	Auto	SMO
SVM-6	rbf	-	5	Auto	ISDA
SVM-7	Polynomial	1	5	Auto	SMO
SVM-8	Polynomial	1	5	Auto	ISDA
SVM-9	Polynomial	2	5	Auto	SMO
SVM-10	Polynomial	2	5	Auto	ISDA
SVM-11	Polynomial	3	5	Auto	SMO
SVM-12	Polynomial	3	5	Auto	ISDA

3.2.3. Multilayer Perceptron Models

The most general form of the multilayer perceptron (MLP) model consists of three layers as seen in Figure 3.5: the input layer, hidden layers, and the output layer. The input layer contains input parameters, and these data are transferred to the hidden layers, which is the second step. The hidden layers process the data coming from the input layer through the neurons inside them and transfer it to the next layer, the output layer, to obtain the result. The number of hidden layers and the neurons they contain may vary. The output layer follows these processes and represents the result section of the model. Here, the result is created using the data processed by the neurons in the hidden layers (Çerçi and Hürdoğan, 2020).

MLP models use different learning algorithms to train the data. The feedforward training algorithm processes the input data and transfers it to the subsequent layers. The backpropagation training algorithm compares the predicted values obtained by the model with the actual values and makes corrections in the previous layers based on these errors. Additionally, various learning algorithms have been developed for different modeling conditions, which vary in terms of time and accuracy. Some of these algorithms include Levenberg-Marquardt (trainlm), scaled conjugate gradient (trainscg), and BFGS quasi-Newton (trainbfg). The MLP models shown in Table 3.4, were created using different learning algorithms, different numbers of hidden layers, and varying numbers of neurons (Parmar and Hindoliya, 2011).

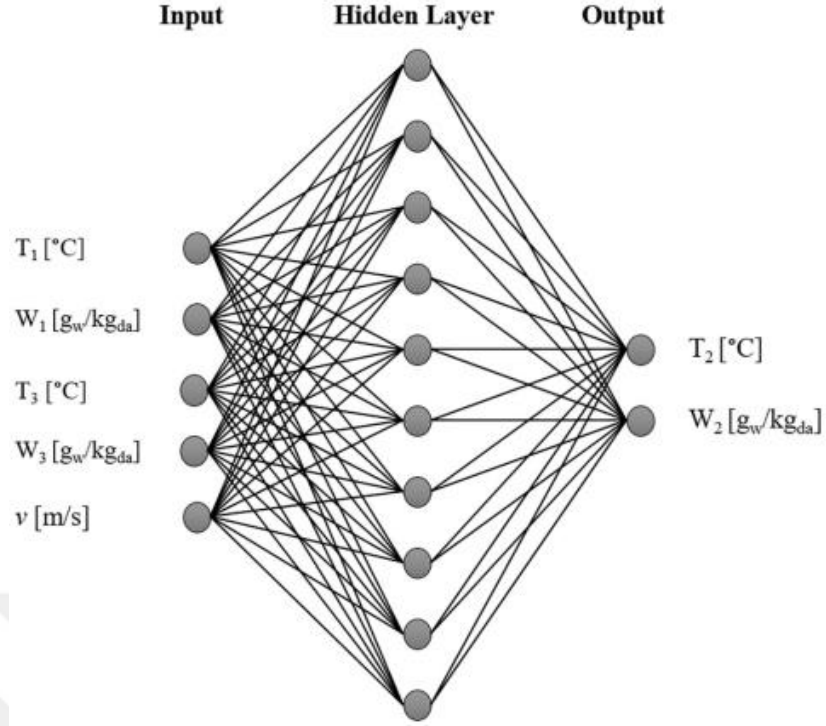


Figure 3.5. Network structure of MLP model (Çerçi and Hürdoğan, 2020).

As shown in Table 3.4, a total of 32 MLP models were examined based on three different parameters: different training functions, the number of hidden layers, and the number of neurons in the hidden layers. Four different training functions were studied: trainlm, trainbfg, trainscg, and trainoss. For these models, two different values were determined for the number of hidden layers: 1 and 2. The number of neurons in each hidden layer was varied from 10 to 40 in increments of 10, resulting in a total of four different neuron counts. In all models, the tansig activation function was selected.

Table 3.4. Input parameters of Multilayer Perceptron models.

Model	Training Function	Layer Number	Neuron Numbers	Activation Function
MLP-1	trainlm	1	10	tansig
MLP-2	trainlm	1	20	tansig
MLP-3	trainlm	1	30	tansig
MLP-4	trainlm	1	40	tansig
MLP-5	trainlm	2	10/10	tansig/tansig
MLP-6	trainlm	2	20/20	tansig/tansig
MLP-7	trainlm	2	30/30	tansig/tansig
MLP-8	trainlm	2	40/40	tansig/tansig
MLP-9	trainbfg	1	10	tansig
MLP-10	trainbfg	1	20	tansig
MLP-11	trainbfg	1	30	tansig
MLP-12	trainbfg	1	40	tansig
MLP-13	trainbfg	2	10/10	tansig/tansig
MLP-14	trainbfg	2	20/20	tansig/tansig
MLP-15	trainbfg	2	30/30	tansig/tansig
MLP-16	trainbfg	2	40/40	tansig/tansig
MLP-17	trainscg	1	10	tansig
MLP-18	trainscg	1	20	tansig
MLP-19	trainscg	1	30	tansig
MLP-20	trainscg	1	40	tansig
MLP-21	trainscg	2	10/10	tansig/tansig
MLP-22	trainscg	2	20/20	tansig/tansig
MLP-23	trainscg	2	30/30	tansig/tansig
MLP-24	trainscg	2	40/40	tansig/tansig
MLP-25	trainoss	1	10	tansig
MLP-26	trainoss	1	20	tansig
MLP-27	trainoss	1	30	tansig
MLP-28	trainoss	1	40	tansig
MLP-29	trainoss	2	10/10	tansig/tansig
MLP-30	trainoss	2	20/20	tansig/tansig
MLP-31	trainoss	2	30/30	tansig/tansig
MLP-32	trainoss	2	40/40	tansig/tansig

3.3. Goodness of Regression Models

In comparing the performance of regression models, the statistical metrics of coefficient of determination (R^2) and root mean squared error (RMSE) are prominently used. R^2 ranges from 0 to 1 and measures how much of the variance in the dependent variable can be explained by the independent variables. If the R^2 value is close to 1, it indicates that the model accurately predicts the dependent variable and thus has a good fit.

RMSE, on the other hand, measures the standard deviation of the differences between the model's predictions and the actual values, representing the average distance between the observed values and the model's predictions. A model with low RMSE values indicates high predictive accuracy. For a model to be considered good, it is expected to have low RMSE and high R^2 values, as these statistical performance parameters reflect the model's accuracy and predictive power (Pham, 2019).

While RMSE and R^2 values provide an overall understanding of the model's performance, anomalies can still occur in specific areas. To detect these anomalies, it is necessary to examine the distributions of relative error (RE). A good regression model is desired to have a high R^2 value and a low RMSE. They are defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (10)$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(Y_i - \hat{Y}_i)^2}{n}} \quad (11)$$

$$RE = \frac{Y_i - \hat{Y}_i}{Y_i} \quad (12)$$

In Equations 10, 11 and 12, n represents the number of data points in the dataset, Y_i is the actual value, $\hat{Y}_i$ is the predicted value, and $\bar{Y}$ is the mean of the actual values (Moore et al., 2009).



4. RESULTS AND DISCUSSIONS

In this study, Multiple Linear Regression (MLR) and Machine Learning (ML) models were developed to predict the temperature and humidity ratio of the process air exiting the desiccant wheel containing LT3 desiccant material. The ML algorithms used included Decision Tree, Support Vector Machine, and Multilayer Perceptron algorithms.

During the model development process, 7 input parameters were varied within the ranges given in Table 3.1 to generate exit conditions of the desiccant wheel for 32,975 different scenarios, using manufacturer data. Using this dataset, a total of 96 models, comprising 7 MLR models, 45 Decision Tree models, 12 Support Vector Machine models, and 32 Multilayer Perceptron models were obtained.

In the following sections of the thesis, the results obtained from the developed models are discussed in detail.

4.1. Comparison of Multiple Linear Regression Models

Tables 4.1 to 4.7 lists the coefficients of the models developed for both process air outlet temperature and humidity ratio. It should be noted that, some coefficients are omitted in the table due to their negligible effect on the output parameters. The number of coefficients for the models varies between 8 and 121.

Table 4.1. Coefficients of 1st Degree model.

Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i
c_0	1.3231495	0.9941732	-
c_1	0.5642422	0.0860081	$T_{p,in}$
c_2	0.7489637	0.6873891	$\omega_{p,in}$
c_3	0.4509797	-0.1032760	$T_{r,in}$
c_4	-0.4956660	0.2110229	$\omega_{r,in}$
c_5	0.2109155	-0.0178820	N
c_6	-5.8076390	1.1393120	$V_{p,in}$
c_7	2.4931969	-0.6810420	$V_{r,in}$

Table 4.2. Coefficients of 2nd Degree model.

Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i
c_0	-2.639843	5.181164	-
c_1	0.589084	0.051682	$T_{p,in}$
c_2	-0.00029	0.000510	$T_{p,in} * T_{p,in}$
c_3	1.443050	0.420093	$\omega_{p,in}$
c_4	-0.02684	0.010321	$\omega_{p,in} * \omega_{p,in}$
c_5	0.503579	-0.147503	$T_{r,in}$
c_6	-0.00036	0.000291	$T_{r,in} * T_{r,in}$
c_7	-0.84065	0.274800	$\omega_{r,in}$
c_8	0.012781	-0.002252	$\omega_{r,in} * \omega_{r,in}$
c_9	0.572303	-0.118836	N
c_{10}	-0.00770	0.002157	$N * N$
c_{11}	-12.6294	2.245001	$V_{p,in}$
c_{12}	1.252586	-0.206340	$V_{p,in} * V_{p,in}$
c_{13}	6.562439	-1.727378	$V_{r,in}$
c_{14}	-0.698333	0.180270	$V_{r,in} * V_{r,in}$

Table 4.3. Coefficients of 3rd Degree model.

Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i
c_0	-70.14788	20.686425	-
c_1	0.572177	0.0520272	$T_{p,in}$
c_2	-	0.0004957	$T_{p,in} * T_{p,in}$
c_3	-	-	$T_{p,in} * T_{p,in} * T_{p,in}$
c_4	1.4728453	0.4184243	$\omega_{p,in}$
c_5	-0.027963	0.0103983	$\omega_{p,in} * \omega_{p,in}$
c_6	-	-	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in}$
c_7	3.118311	-0.707087	$T_{r,in}$
c_8	-0.034172	0.007526	$T_{r,in} * T_{r,in}$
c_9	0.0001447	-0.000031	$T_{r,in} * T_{r,in} * T_{r,in}$
c_{10}	-1.174762	0.2690913	$\omega_{r,in}$
c_{11}	0.0415093	-0.002043	$\omega_{r,in} * \omega_{r,in}$
c_{12}	-0.000777	-	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in}$
c_{13}	1.0392848	-0.261198	N
c_{14}	-0.031177	0.0092933	$N * N$
c_{15}	0.00033	-0.0001	$N * N * N$
c_{16}	-18.03447	2.8114062	$V_{p,in}$
c_{17}	3.425534	-0.446624	$V_{p,in} * V_{p,in}$
c_{18}	-0.264551	0.0294709	$V_{p,in} * V_{p,in} * V_{p,in}$
c_{19}	11.212975	-2.777862	$V_{r,in}$
c_{20}	-2.396074	0.5643647	$V_{r,in} * V_{r,in}$
c_{21}	0.1784249	-0.040437	$V_{r,in} * V_{r,in} * V_{r,in}$

Table 4.4. Coefficients of 1st Degree Cross model.

Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i
c_0	1.7547032	-2.111256	-
c_1	0.5162578	0.0877705	$T_{p,in}$
c_2	0.3349726	0.832886	$\omega_{p,in}$
c_3	0.4028819	-0.052149	$T_{r,in}$
c_4	-0.378866	0.2829323	$\omega_{r,in}$
c_5	0.121549	0.0586638	N
c_6	-0.812935	0.1091283	$V_{p,in}$
c_7	0.9090281	-0.491259	$V_{r,in}$
c_8	-	-0.000671	$T_{p,in} * \omega_{p,in}$
c_9	0.0005674	-	$T_{p,in} * T_{r,in}$
c_{10}	-0.005573	0.0013229	$T_{p,in} * \omega_{r,in}$
c_{11}	-0.007196	0.0008751	$T_{p,in} * N$
c_{12}	0.1122018	-0.019002	$T_{p,in} * V_{p,in}$
c_{13}	-0.028041	0.0084098	$T_{p,in} * V_{r,in}$
c_{14}	0.0098176	-0.003268	$\omega_{p,in} * T_{r,in}$
c_{15}	-0.012445	0.0070662	$\omega_{p,in} * \omega_{r,in}$
c_{16}	0.0093061	-0.007589	$\omega_{p,in} * N$
c_{17}	-	-	$\omega_{p,in} * V_{p,in}$
c_{18}	-0.134112	0.0708918	$\omega_{p,in} * V_{r,in}$
c_{19}	0.0015529	-0.002273	$T_{r,in} * \omega_{r,in}$
c_{20}	0.0015953	0.0002969	$T_{r,in} * N$
c_{21}	-0.094012	0.0161178	$T_{r,in} * V_{p,in}$
c_{22}	0.0404941	-0.010726	$T_{r,in} * V_{r,in}$
c_{23}	0.0006651	0.0030775	$\omega_{r,in} * N$
c_{24}	-0.180848	0.0621447	$\omega_{r,in} * V_{p,in}$
c_{25}	0.2205229	-0.100217	$\omega_{r,in} * V_{r,in}$
c_{26}	-	-0.016865	$N * V_{p,in}$
c_{27}	0.0222308	-0.00594	$N * V_{r,in}$
c_{28}	0.6092757	-0.061936	$V_{p,in} * V_{r,in}$
c_{29}	-0.748384	0.1890371	$V_{r,in} * V_{r,in}$

Table 4.5. Coefficients of 2nd Degree Cross model.

Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i	Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i
C_0	5.79827	1.76002	Intercept	C_{39}	-0.00675	0.00352	$T_{r,in} * N$
C_1	0.69528	-0.02387	$T_{p,in}$	C_{40}	-0.10926	0.02237	$T_{r,in} * V_{p,in}$
C_2	-0.00263	0.00133	$T_{p,in} * T_{p,in}$	C_{41}	0.16635	-0.05936	$T_{r,in} * V_{r,in}$
C_3	0.44990	0.57602	$\omega_{p,in}$	C_{42}	-	-	$T_{r,in} * T_{r,in} * T_{p,in}$
C_4	-0.01103	0.00872	$\omega_{p,in} * \omega_{p,in}$	C_{43}	-	-	$T_{r,in} * T_{r,in} * \omega_{p,in}$
C_5	0.30214	-0.12807	$T_{r,in}$	C_{44}	-	-0.00003	$T_{r,in} * T_{r,in} * \omega_{r,in}$
C_6	0.00043	0.00076	$T_{r,in} * T_{r,in}$	C_{45}	0.00007	-0.00003	$T_{r,in} * T_{r,in} * N$
C_7	-0.41514	0.32002	$\omega_{r,in}$	C_{46}	-0.00046	-	$T_{r,in} * T_{r,in} * V_{p,in}$
C_8	-0.01335	-0.00143	$\omega_{r,in} * \omega_{r,in}$	C_{47}	-0.00042	0.00023	$T_{r,in} * T_{r,in} * V_{r,in}$
C_9	0.58182	-0.03977	N	C_{48}	-0.00654	0.00727	$\omega_{r,in} * N$
C_{10}	0.00022	-0.00038	$N * N$	C_{49}	-0.44852	-0.11596	$\omega_{r,in} * V_{p,in}$
C_{11}	-8.17418	1.24153	$V_{p,in}$	C_{50}	0.57258	-	$\omega_{r,in} * V_{r,in}$
C_{12}	1.61605	-0.37209	$V_{p,in} * V_{p,in}$	C_{51}	-	-	$\omega_{r,in} * \omega_{r,in} * T_{p,in}$
C_{13}	-1.10002	0.99800	$V_{r,in}$	C_{52}	0.00035	-0.00016	$\omega_{r,in} * \omega_{r,in} * \omega_{p,in}$
C_{14}	-2.31277	0.56850	$V_{r,in} * V_{r,in}$	C_{53}	0.00029	-	$\omega_{r,in} * \omega_{r,in} * T_{r,in}$
C_{15}	-0.01165	0.00490	$T_{p,in} * \omega_{p,in}$	C_{54}	0.00013	-0.00008	$\omega_{r,in} * \omega_{r,in} * N$
C_{16}	0.00051	-	$T_{p,in} * T_{r,in}$	C_{55}	0.00564	-0.00194	$\omega_{r,in} * \omega_{r,in} * V_{p,in}$
C_{17}	0.00770	-0.00232	$T_{p,in} * \omega_{r,in}$	C_{56}	-0.00852	0.00286	$\omega_{r,in} * \omega_{r,in} * V_{r,in}$
C_{18}	-0.02487	0.00500	$T_{p,in} * N$	C_{57}	0.00883	-0.05093	$N * V_{p,in}$
C_{19}	0.22272	-0.02602	$T_{p,in} * V_{p,in}$	C_{58}	0.13293	-0.03679	$N * V_{r,in}$
C_{20}	-0.06426	0.01451	$T_{p,in} * V_{r,in}$	C_{59}	0.00025	-0.00006	$N * N * T_{p,in}$
C_{21}	0.00019	-0.00009	$T_{p,in} * T_{p,in} * \omega_{p,in}$	C_{60}	-0.00079	0.00023	$N * N * \omega_{p,in}$
C_{22}	-	-	$T_{p,in} * T_{p,in} * T_{r,in}$	C_{61}	-0.00006	0.00002	$N * N * T_{r,in}$
C_{23}	-0.00019	0.00005	$T_{p,in} * T_{p,in} * \omega_{r,in}$	C_{62}	0.00010	-0.00005	$N * N * \omega_{r,in}$
C_{24}	0.00008	-0.00002	$T_{p,in} * T_{p,in} * N$	C_{63}	-0.00028	0.00039	$N * N * V_{p,in}$
C_{25}	-	-	$T_{p,in} * T_{p,in} * V_{p,in}$	C_{64}	-0.00108	-0.26998	$N * N * V_{r,in}$
C_{26}	-	-	$T_{p,in} * T_{p,in} * V_{r,in}$	C_{65}	1.56585	-	$V_{p,in} * V_{r,in}$
C_{27}	0.02755	-0.00764	$\omega_{p,in} * T_{r,in}$	C_{66}	-0.01911	0.00119	$V_{p,in} * V_{p,in} * T_{p,in}$
C_{28}	-0.00654	0.00846	$\omega_{p,in} * \omega_{r,in}$	C_{67}	-	-0.00843	$V_{p,in} * V_{p,in} * \omega_{p,in}$
C_{29}	0.03930	-0.01947	$\omega_{p,in} * N$	C_{68}	0.01486	-0.00123	$V_{p,in} * V_{p,in} * T_{r,in}$
C_{30}	-	0.27538	$\omega_{p,in} * V_{p,in}$	C_{69}	0.02723	-	$V_{p,in} * V_{p,in} * \omega_{r,in}$
C_{31}	-0.43493	-0.06390	$\omega_{p,in} * V_{r,in}$	C_{70}	-	0.00595	$V_{p,in} * V_{p,in} * N$
C_{32}	-	-	$\omega_{p,in} * \omega_{p,in} * T_{p,in}$	C_{71}	-0.73557	0.15555	$V_{p,in} * V_{p,in} * V_{r,in}$
C_{33}	-0.00068	0.00016	$\omega_{p,in} * \omega_{p,in} * T_{r,in}$	C_{72}	0.00569	-0.00104	$V_{r,in} * V_{r,in} * T_{p,in}$
C_{34}	-	-0.00014	$\omega_{p,in} * \omega_{p,in} * \omega_{r,in}$	C_{73}	0.02515	-0.00841	$V_{r,in} * V_{r,in} * \omega_{p,in}$
C_{35}	0.00040	-	$\omega_{p,in} * \omega_{p,in} * N$	C_{74}	-0.00917	0.00203	$V_{r,in} * V_{r,in} * T_{r,in}$
C_{36}	-	-	$\omega_{p,in} * \omega_{p,in} * V_{p,in}$	C_{75}	-0.02743	0.00933	$V_{r,in} * V_{r,in} * \omega_{r,in}$
C_{37}	0.00594	-0.00146	$\omega_{p,in} * \omega_{p,in} * V_{r,in}$	C_{76}	-0.00710	0.00147	$V_{r,in} * V_{r,in} * N$
C_{38}	-0.00687	0.00221	$T_{r,in} * \omega_{r,in}$	C_{77}	0.63277	-0.14926	$V_{r,in} * V_{r,in} * V_{p,in}$

Table 4.6. Coefficients of 3rd Degree Cross model.

Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i	Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$	X_i	Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$	X_i
C0	10.684235	-0.938962	-	C43	-	-	$\omega_{p,in} * V_{p,in}$	C86	0.000771	-0.000281	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in} * V_{p,in}$
C1	0.949754	-0.147506	$T_{p,in}$	C44	-0.441473	0.226409	$\omega_{p,in} * V_{r,in}$	C87	-0.000203	0.000176	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in} * V_{r,in}$
C2	0.006080	0.002453	$T_{p,in} * T_{p,in}$	C45	-0.000979	-0.000042	$\omega_{p,in} * \omega_{p,in} * T_{p,in}$	C88	-0.022614	-0.075574	$N * V_{p,in}$
C3	-0.000077	-0.000008	$T_{p,in} * T_{p,in} * T_{p,in}$	C46	-0.000131	-0.000068	$\omega_{p,in} * \omega_{p,in} * T_{r,in}$	C89	0.363855	-0.097449	$N * V_{r,in}$
C4	-14.296910	4.747348	$\omega_{p,in}$	C47	-0.004617	0.001175	$\omega_{p,in} * \omega_{p,in} * \omega_{r,in}$	C90	0.000954	-0.000244	$N * N * T_{p,in}$
C5	-0.028639	0.026109	$\omega_{p,in} * \omega_{p,in}$	C48	0.004479	-0.001220	$\omega_{p,in} * \omega_{p,in} * N$	C91	-0.003454	0.000958	$N * N * \omega_{p,in}$
C6	0.000495	-0.000488	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in}$	C49	-	-	$\omega_{p,in} * \omega_{p,in} * V_{p,in}$	C92	-0.000151	0.000091	$N * N * T_{r,in}$
C7	0.179524	0.117751	$T_{r,in}$	C50	-0.012944	0.006829	$\omega_{p,in} * \omega_{p,in} * V_{r,in}$	C93	0.000156	-0.000115	$N * N * \omega_{r,in}$
C8	0.002999	-0.002483	$T_{r,in} * T_{r,in}$	C51	0.000027	-	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in} * T_{p,in}$	C94	0.001033	-0.000646	$N * N * V_{p,in}$
C9	-0.000017	0.000015	$T_{r,in} * T_{r,in} * T_{r,in}$	C52	-0.000015	0.000006	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in} * T_{r,in}$	C95	-0.006747	0.002230	$N * N * V_{r,in}$
C10	11.012362	-4.364280	$\omega_{r,in}$	C53	0.000129	-0.000033	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in} * \omega_{r,in}$	C96	-0.000010	0.000002	$N * N * N * T_{p,in}$
C11	-0.122587	0.083729	$\omega_{r,in} * \omega_{r,in}$	C54	-0.000106	0.000032	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in} * N$	C97	0.000036	-0.000010	$N * N * N * \omega_{p,in}$
C12	0.003013	-0.002328	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in}$	C55	-	-	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in} * V_{p,in}$	C98	0.000001	-0.000001	$N * N * N * T_{r,in}$
C13	-2.068697	0.675830	N	C56	0.000464	-0.000210	$\omega_{p,in} * \omega_{p,in} * \omega_{p,in} * V_{r,in}$	C99	-0.000001	0.000001	$N * N * N * \omega_{r,in}$
C14	0.004419	-0.003793	$N * N$	C57	-0.446784	0.167712	$T_{r,in} * \omega_{r,in}$	C100	-0.000018	0.000009	$N * N * N * V_{p,in}$
C15	-0.000045	0.000043	$N * N * N$	C58	0.097504	-0.021791	$T_{r,in} * N$	C101	0.000075	-0.000024	$N * N * N * V_{r,in}$
C16	7.791235	-1.401498	$V_{p,in}$	C59	-1.170793	0.195736	$T_{r,in} * V_{p,in}$	C102	7.825342	-1.804569	$V_{p,in} * V_{r,in}$
C17	5.870831	-1.145100	$V_{p,in} * V_{p,in}$	C60	0.012836	-0.014872	$T_{r,in} * V_{r,in}$	C103	-0.080309	0.002084	$V_{p,in} * V_{p,in} * T_{p,in}$
C18	-0.611307	0.113334	$V_{p,in} * V_{p,in} * V_{p,in}$	C61	0.000243	-0.000005	$T_{r,in} * T_{r,in} * T_{p,in}$	C104	-	-	$V_{p,in} * V_{p,in} * \omega_{p,in}$
C19	1.757881	0.235685	$V_{r,in}$	C62	-0.008130	0.002444	$T_{r,in} * T_{r,in} * \omega_{p,in}$	C105	0.062827	-0.007632	$V_{p,in} * V_{p,in} * T_{r,in}$
C20	-6.737560	1.563888	$V_{r,in} * V_{r,in}$	C63	0.005485	-0.002009	$T_{r,in} * T_{r,in} * \omega_{r,in}$	C106	0.155584	-0.036827	$V_{p,in} * V_{p,in} * \omega_{r,in}$
C21	0.853718	-0.197758	$V_{r,in} * V_{r,in} * V_{r,in}$	C64	-0.001257	0.000283	$T_{r,in} * T_{r,in} * N$	C107	0.005636	0.019128	$V_{p,in} * V_{p,in} * N$
C22	-0.088589	0.050915	$T_{p,in} * \omega_{p,in}$	C65	0.011486	-0.002029	$T_{r,in} * T_{r,in} * V_{p,in}$	C108	-4.301574	0.977734	$V_{p,in} * V_{p,in} * V_{r,in}$
C23	-0.008775	-0.003573	$T_{p,in} * T_{r,in}$	C66	0.002958	-0.000642	$T_{r,in} * T_{r,in} * V_{r,in}$	C109	0.006980	-	$V_{p,in} * V_{p,in} * V_{p,in} * T_{p,in}$
C24	0.036372	-0.010982	$T_{p,in} * \omega_{r,in}$	C67	-0.000001	-	$T_{r,in} * T_{r,in} * T_{r,in} * T_{p,in}$	C110	-	-	$V_{p,in} * V_{p,in} * V_{p,in} * \omega_{p,in}$
C25	-0.033553	0.004727	$T_{p,in} * N$	C68	0.000035	-0.000010	$T_{r,in} * T_{r,in} * T_{r,in} * \omega_{p,in}$	C111	-0.005456	0.000703	$V_{p,in} * V_{p,in} * V_{p,in} * T_{r,in}$
C26	0.267938	0.016428	$T_{p,in} * V_{p,in}$	C69	-0.000024	0.000008	$T_{r,in} * T_{r,in} * T_{r,in} * \omega_{r,in}$	C112	-0.014600	0.003006	$V_{p,in} * V_{p,in} * V_{p,in} * \omega_{r,in}$
C27	-0.048960	0.018799	$T_{p,in} * V_{r,in}$	C70	0.000006	-0.000001	$T_{r,in} * T_{r,in} * T_{r,in} * N$	C113	-0.000894	-0.001506	$V_{p,in} * V_{p,in} * V_{p,in} * N$
C28	0.003002	-0.001515	$T_{p,in} * T_{p,in} * \omega_{p,in}$	C71	-0.000051	0.000009	$T_{r,in} * T_{r,in} * T_{r,in} * V_{p,in}$	C114	0.459509	-0.104185	$V_{p,in} * V_{p,in} * V_{p,in} * V_{r,in}$
C29	-0.000366	0.000144	$T_{p,in} * T_{p,in} * T_{r,in}$	C72	-0.000014	0.000004	$T_{r,in} * T_{r,in} * T_{r,in} * V_{r,in}$	C115	0.027693	-0.003453	$V_{r,in} * V_{r,in} * T_{p,in}$
C30	-0.001358	0.000471	$T_{p,in} * T_{p,in} * \omega_{r,in}$	C73	-0.025385	0.012607	$\omega_{r,in} * N$	C116	0.118282	-0.060165	$V_{r,in} * V_{r,in} * \omega_{p,in}$
C31	-0.000094	0.000110	$T_{p,in} * T_{p,in} * N$	C74	-0.430298	0.113093	$\omega_{r,in} * V_{p,in}$	C117	-0.044436	0.009840	$V_{r,in} * V_{r,in} * T_{r,in}$
C32	0.004116	-0.001404	$T_{p,in} * T_{p,in} * V_{p,in}$	C75	0.803084	-0.336272	$\omega_{r,in} * V_{r,in}$	C118	-0.146228	0.067882	$V_{r,in} * V_{r,in} * \omega_{r,in}$
C33	-0.002485	0.000070	$T_{p,in} * T_{p,in} * V_{r,in}$	C76	0.000589	-0.000376	$\omega_{r,in} * \omega_{r,in} * T_{p,in}$	C119	-0.043084	0.008386	$V_{r,in} * V_{r,in} * N$
C34	-0.000029	0.000015	$T_{p,in} * T_{p,in} * T_{p,in} * \omega_{p,in}$	C77	0.000844	-0.000095	$\omega_{r,in} * \omega_{r,in} * \omega_{p,in}$	C120	2.138532	-0.488890	$V_{r,in} * V_{r,in} * V_{p,in}$
C35	0.000004	-0.000002	$T_{p,in} * T_{p,in} * T_{p,in} * T_{r,in}$	C78	0.001924	-0.001020	$\omega_{r,in} * \omega_{r,in} * T_{r,in}$	C121	-0.002058	0.000193	$V_{r,in} * V_{r,in} * V_{r,in} * T_{p,in}$
C36	0.000012	-0.000004	$T_{p,in} * T_{p,in} * T_{p,in} * \omega_{r,in}$	C79	0.001788	-0.000457	$\omega_{r,in} * \omega_{r,in} * N$	C122	-0.011089	0.005061	$V_{r,in} * V_{r,in} * V_{r,in} * \omega_{p,in}$
C37	0.000002	-0.000001	$T_{p,in} * T_{p,in} * T_{p,in} * N$	C80	-0.024802	0.008926	$\omega_{r,in} * \omega_{r,in} * V_{p,in}$	C123	0.003394	-0.000743	$V_{r,in} * V_{r,in} * V_{r,in} * T_{r,in}$
C38	-0.000045	0.000014	$T_{p,in} * T_{p,in} * T_{p,in} * V_{p,in}$	C81	-0.000765	-0.003724	$\omega_{r,in} * \omega_{r,in} * V_{r,in}$	C124	0.013577	-0.005696	$V_{r,in} * V_{r,in} * V_{r,in} * \omega_{r,in}$
C39	0.000024	-	$T_{p,in} * T_{p,in} * T_{p,in} * V_{r,in}$	C82	-0.000013	0.000010	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in} * T_{p,in}$	C125	0.003522	-0.000678	$V_{r,in} * V_{r,in} * V_{r,in} * N$
C40	0.645609	-0.194611	$\omega_{p,in} * T_{r,in}$	C83	-0.000015	-	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in} * \omega_{p,in}$	C126	-0.256746	0.059224	$V_{r,in} * V_{r,in} * V_{r,in} * V_{p,in}$
C41	0.036113	-0.008599	$\omega_{p,in} * \omega_{r,in}$	C84	-0.000044	0.000027	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in} * T_{r,in}$	-	-	-	-
C42	0.044723	-0.019831	$\omega_{p,in} * N$	C85	-0.000044	0.000010	$\omega_{r,in} * \omega_{r,in} * \omega_{r,in} * N$	-	-	-	-

Table 4.7. Coefficients of Response Surface model.

Estimates	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	X_i
C_0	-1.324345	1.5762473	-
C_1	0.5824081	0.052344	$T_{p,in}$
C_2	1.0663891	0.553203	$\omega_{p,in}$
C_3	0.4679598	-0.109768	$T_{r,in}$
C_4	-0.853564	0.4388322	$\omega_{r,in}$
C_5	0.4987369	-0.053857	N
C_6	-6.45939	0.8440485	$V_{p,in}$
C_7	2.688596	-0.678296	$V_{r,in}$
C_8	-0.00088	0.000547	$T_{p,in} * T_{p,in}$
C_9	-	-0.000864	$T_{p,in} * \omega_{p,in}$
C_{10}	-0.037339	0.0148851	$\omega_{p,in} * \omega_{p,in}$
C_{11}	0.0003659	-	$T_{p,in} * T_{r,in}$
C_{12}	0.0105409	-0.00369	$\omega_{p,in} * T_{r,in}$
C_{13}	-0.000319	0.00038	$T_{r,in} * T_{r,in}$
C_{14}	-0.004396	0.001245	$T_{p,in} * \omega_{r,in}$
C_{15}	-0.002184	0.0017744	$\omega_{p,in} * \omega_{r,in}$
C_{16}	0.0007175	-0.002015	$T_{r,in} * \omega_{r,in}$
C_{17}	0.0113042	-0.003169	$\omega_{r,in} * \omega_{r,in}$
C_{18}	-0.007978	0.0011171	$T_{p,in} * N$
C_{19}	0.0129902	-0.008858	$\omega_{p,in} * N$
C_{20}	0.0011701	0.0004487	$T_{r,in} * N$
C_{21}	0.0014885	0.0028569	$\omega_{r,in} * N$
C_{22}	-0.008805	0.00268	$N * N$
C_{23}	0.116457	-0.019347	$T_{p,in} * V_{p,in}$
C_{24}	-	-	$\omega_{p,in} * V_{p,in}$
C_{25}	-0.099259	0.0162146	$T_{r,in} * V_{p,in}$
C_{26}	-0.153584	0.0617653	$\omega_{r,in} * V_{p,in}$
C_{27}	-0.003636	-0.017701	$N * V_{p,in}$
C_{28}	1.2511171	-0.148954	$V_{p,in} * V_{p,in}$
C_{29}	-0.029306	0.008084	$T_{p,in} * V_{r,in}$
C_{30}	-0.143837	0.0796609	$\omega_{p,in} * V_{r,in}$
C_{31}	0.045925	-0.011551	$T_{r,in} * V_{r,in}$
C_{32}	0.2063601	-0.103681	$\omega_{r,in} * V_{r,in}$
C_{33}	0.038727	-0.009827	$N * V_{r,in}$
C_{34}	-	-0.011151	$V_{p,in} * V_{r,in}$
C_{35}	-0.771781	0.2063836	$V_{r,in} * V_{r,in}$

The RMSE and R^2 values of the seven MLR models are compared in Table 4.8. Additionally, the number of coefficients, which affects the ease of use of the MLR models, is also presented in the same table. Among the generated models, the 1st Degree model has the fewest coefficients (8 coefficients), making it the easiest to use. However, it also exhibits the highest error (RMSE) and the lowest R^2 values for both $T_{p,out}$ and $\omega_{p,out}$. Specifically, the RMSE values are as high as 2.293 °C for $T_{p,out}$ and 0.6948 g/kg for $\omega_{p,out}$. The R^2 values are 0.90 for $T_{p,out}$ and 0.96 for $\omega_{p,out}$.

As the degree of the model increases, improvements in RMSE and R^2 values are observed along with an increase in the number of coefficients. For instance, the RMSE and R^2 values for $T_{p,out}$ in the 1st Degree model are 2.2930 °C and 0.90, respectively, whereas these values improve to 1.5652 °C and 0.96 in the 3rd Degree model. Similarly, increasing the equation's degree from one to three reduces the RMSE value for $\omega_{p,out}$ from 0.6948 g/kg to 0.5312 g/kg.

The addition of cross terms to the models lead to a significant increase in the number of coefficients. Adding cross terms to the 3rd Degree model increases its coefficients from 22 to 121. Despite reducing ease of use due to the increased number of coefficients, this enhancement greatly improves the model's performance. Comparing the 3rd Degree Cross model to the 3rd Degree model, the RMSE values for $T_{p,out}$ and $\omega_{p,out}$ decrease by 0.6534 °C and 0.3538 g/kg, respectively. Additionally, the R^2 value increases from 0.9600 to 0.9934 for $T_{p,out}$ and from 0.9700 to 0.9971 for $\omega_{p,out}$.

The 3rd Degree Cross model yields the best RMSE and R^2 results among the models. It has the highest number of coefficients (121) compared to other models, with RMSE and R^2 values of 0.6018 °C and 0.99344 for $T_{p,out}$, and 0.1774 g/kg and 0.99715 for $\omega_{p,out}$. In comparison, the Response Surface model, despite having fewer coefficients (36) than the 3rd Degree Cross model, performs quite well. This model stands out in terms of ease of use and accuracy.

In summary, as the degree of the model and the addition of cross terms increase, the number of coefficients also increases. This, however, reduces ease of use. Nevertheless, adding cross terms significantly improves model performance. While the 3rd Degree Cross model achieves the highest accuracy, the Response Surface model performs well with fewer coefficients (36). Despite reducing the number of coefficients from 121 to 36, there is a slight increase in RMSE value by 0.4614 °C for $T_{p,out}$, and the R^2 value decreases from 0.99344 to 0.98. The same trend applies to $\omega_{p,out}$. When considering ease of use, this slight decrease in the performance of the model can be considered negligible.

Table 4.8. Comparison of Multiple Linear Regression models.

Model	RMSE		R^2		No of coef.
	$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	$T_{p,out}$	$\omega_{p,out}$	
1 st Degree	2.2930	0.6948	0.9000	0.9600	8
1 st Degree Cross	1.6737	0.4769	0.9500	0.9800	29
2 nd Degree	1.6685	0.5526	0.9500	0.9700	15
2 nd Degree Cross	0.8822	0.2515	0.9859	0.9943	70
3 rd Degree	1.5652	0.5312	0.9600	0.9700	22
3rd Degree Cross	0.6018	0.1774	0.9934	0.9972	121
Response Surface	1.0632	0.2998	0.9800	0.9919	36

In Figures 4.1 to 4.7, the prediction data generated through the developed models are compared with the actual data. For example, in Figure 4.1a, the process air outlet temperatures ($T_{p,out}$) generated by the 1st Degree model are compared with the actual values, and the $\pm 5\%$, $\pm 10\%$, and $\pm 15\%$ error bands are shown. Figure 4.1b presents a histogram of the relative errors of the generated data from the model. Similar figures for $\omega_{p,out}$ are illustrated in Figures 4.1c and 4.1d.

When examining Figure 4.1a, it is observed that the 1st Degree model generates temperature data outside the $\pm 15\%$ error band. Additionally, 0.5% of the predicted temperature data has a relative error greater than 19% (Figure 4.1b).

Figure 4.1c shows that the 1st Degree model produces highly erroneous results, particularly in low humidity regions where the humidity ratio is less than approximately 5 g/kg. Figure 4.1d shows that the data is distributed across all specified error ranges. Here, 0.9% of the predicted humidity ratio data has a relative error greater than 19% (Figure 4.1d).

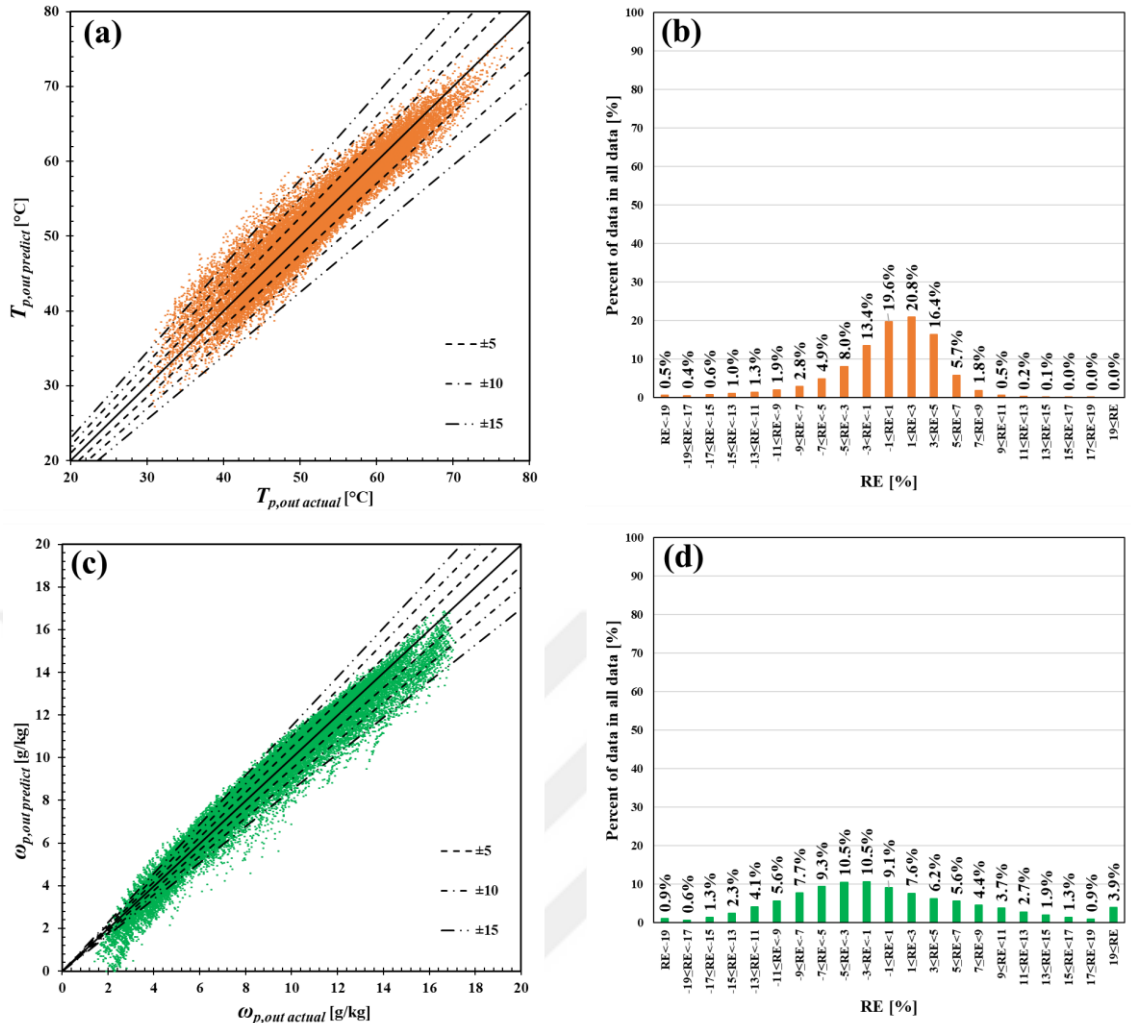


Figure 4.1. Comparison of predicted data from 1st Degree model with actual data.

After adding cross terms to the 1st Degree model, a significant reduction in the number of predicted data points outside the $\pm 15\%$ error band, as shown in Figure 4.2a compared to Figure 4.1a is observed. With the addition of cross terms, the distribution of predicted data, as shown in Figure 4.2b, is concentrated in the low-error regions at the center, compared to Figure 4.1b. For the process outlet temperature, the percentage of data within the $\pm 3\%$ error range is 67.6%, an increase of 13.8% compared to the 1st Degree model. Similar improvements are observed for the humidity ratio (Figures 4.2c and 4.2d), with an increase of 9.1%, resulting in 36.3% of the total data falling within this range.

The addition of cross terms has improved the prediction accuracy of the developed model in low humidity regions, as seen in Figure 4.2c.

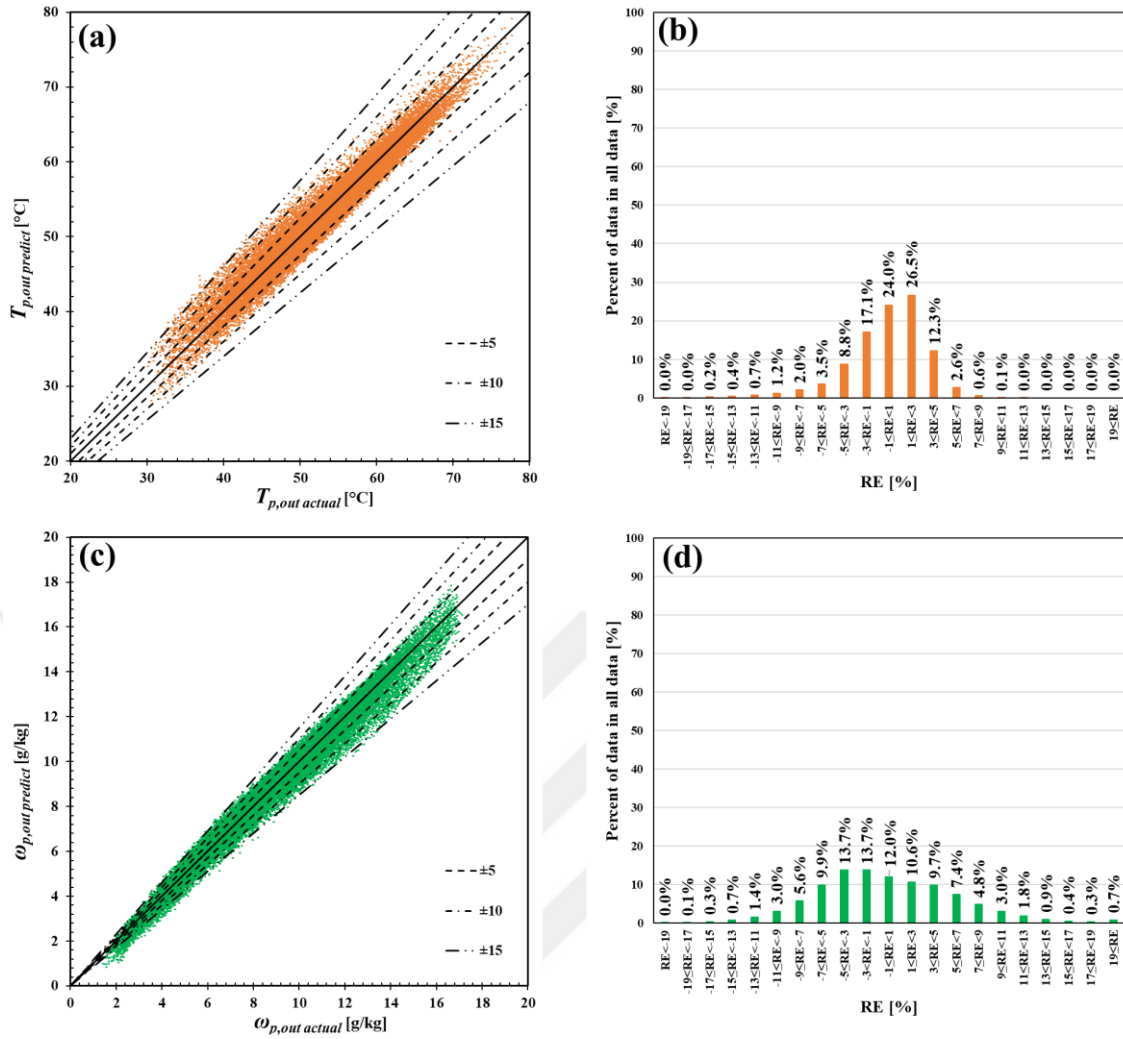


Figure 4.2. Comparison of predicted data from 1st Degree Cross model with actual data.

Comparison of the 1st Degree model (Figure 4.1a) with the 2nd Degree model (Figure 4.3a), it is observed that the 2nd Degree model has fewer predicted data points exceeding the $\pm 15\%$ error band for $T_{p,out}$. Additionally, a reduction in the number of data points with high error rates produced by the model is observed (Figure 4.3b).

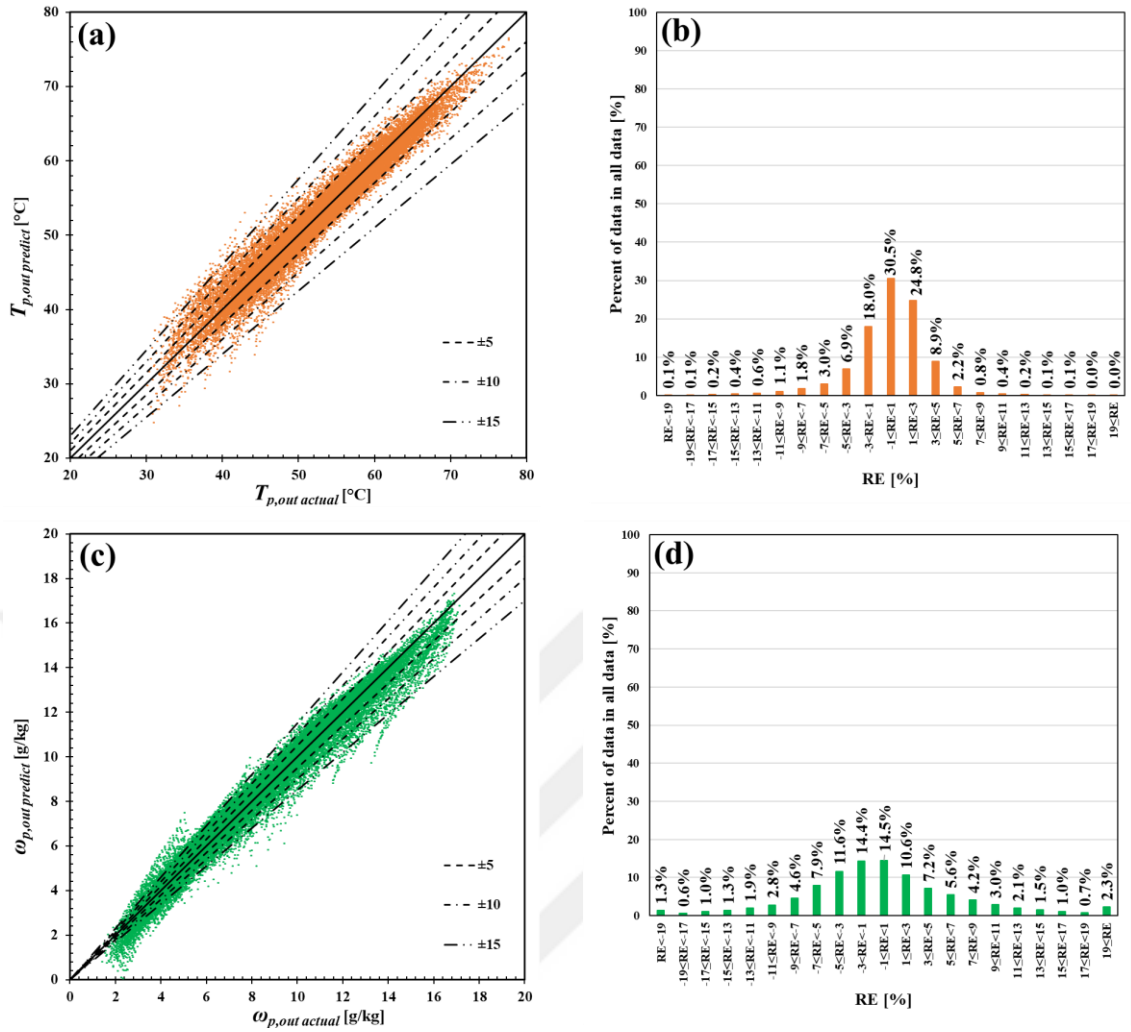


Figure 4.3. Comparison of predicted data from 2nd Degree model with actual data.

In the 2nd Degree Cross model shown in Figure 4.4, the accuracy of the data generated by the model has significantly improved compared to the previous models (1st Degree, 1st Degree Cross, 2nd Degree). For $T_{p,out}$, nearly all data points fall within the $\pm 10\%$ error band (Figure 4.4a). Additionally, as shown in Figure 4.4b, 91.6% of the generated data ($T_{p,out}$) falls within the $\pm 3\%$ error range. Furthermore, the 2nd Degree Cross model provides more accurate predictions for $w_{p,out}$ in low humidity regions compared to the previous models (Figure 4.4c).

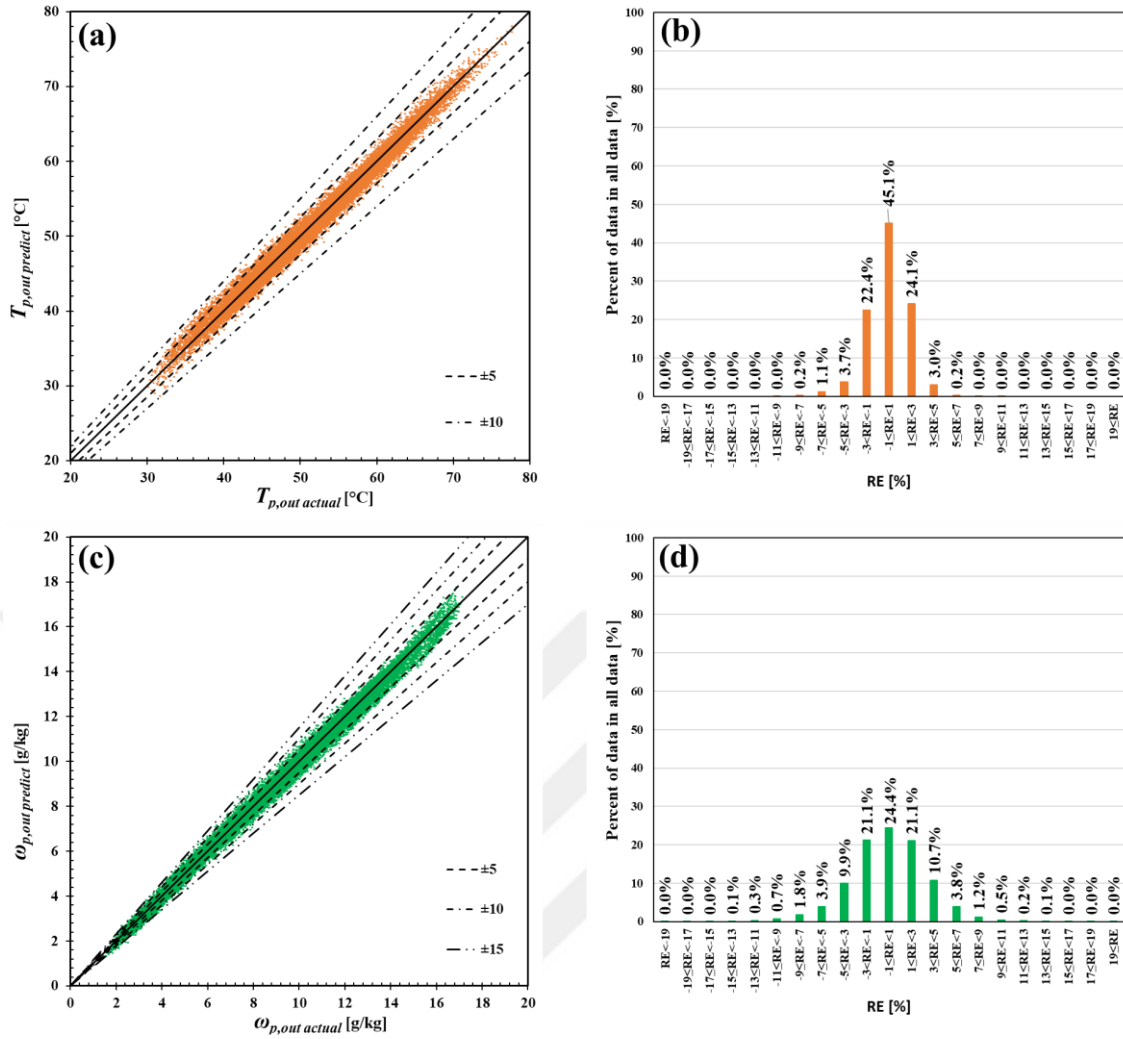


Figure 4.4. Comparison of predicted data from 2nd Degree Cross model with actual data.

According to Figure 4.5a, even though the majority of $T_{p,out}$ data points generated by the 3rd Degree model fall within the $\pm 15\%$ error band, there are still some data points exceeding this error band. For the process outlet temperature ($T_{p,out}$), 76.2% of the generated data is within the $\pm 3\%$ error range. For the process outlet humidity ratio ($\omega_{p,out}$), 41.6% of the generated data falls within the $\pm 3\%$ error range. These values are 22.4% higher for process outlet temperature compared to the 1st Degree model and 3.2% higher than the 2nd Degree model. For the process outlet humidity ratio, these values are 14.4% higher than the 1st Degree model and 2.1% higher than the 2nd Degree model.

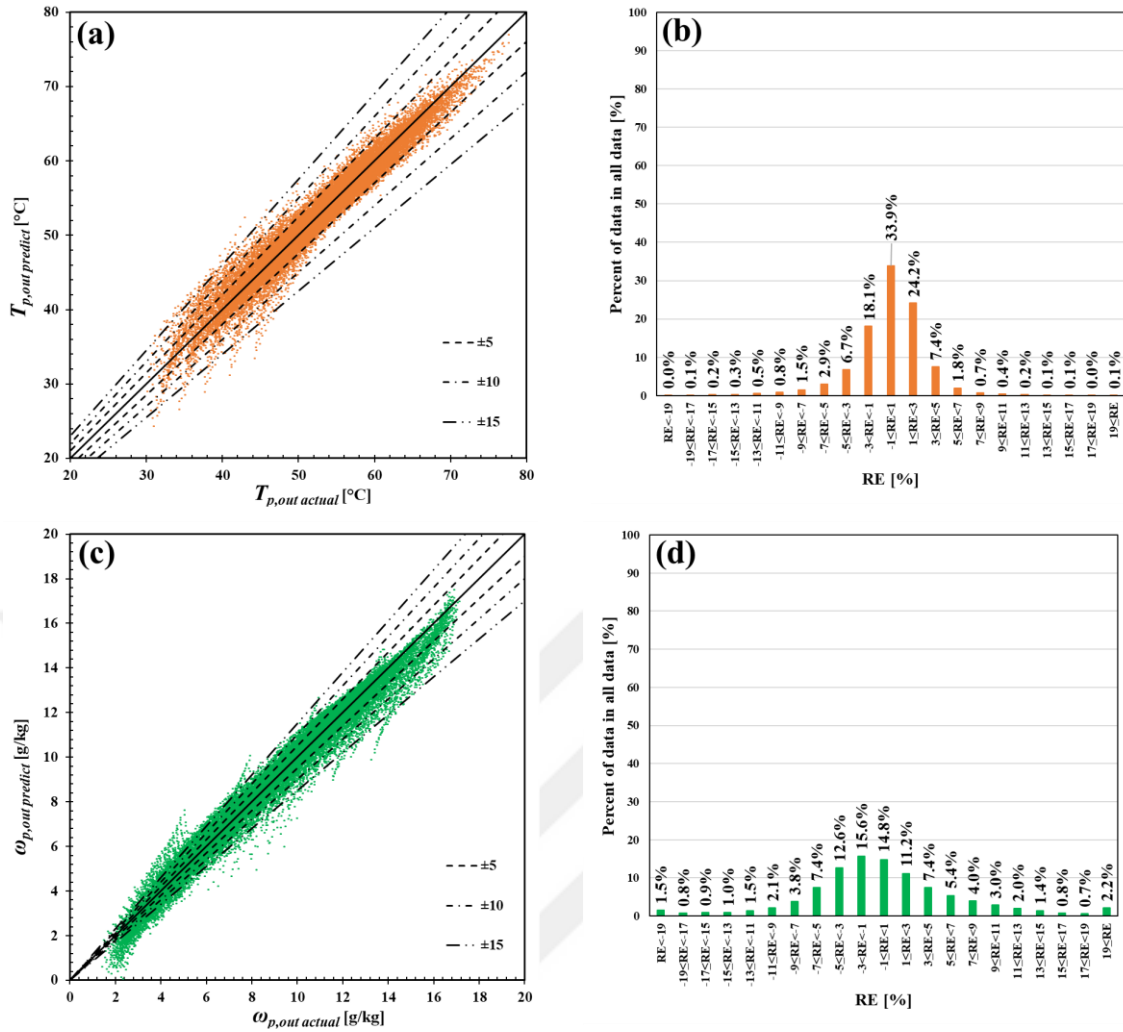


Figure 4.5. Comparison of predicted data from 3rd Degree model with actual data.

A comparison of the generated data through the 3rd Degree Cross model and actual data, which has the best results in terms of RMSE and R^2 values, is presented in Figure 4.6. Compared to the other models, the majority of the $T_{p,out}$ and $\omega_{p,out}$ data is concentrated within the $\pm 5\%$ error band (Figure 4.6a and Figure 4.6c). For temperature, 97.2% of the generated data falls within the $\pm 3\%$ error range (Figure 4.6b). For humidity ratio, this value is 82.4% (Figure 4.6d)

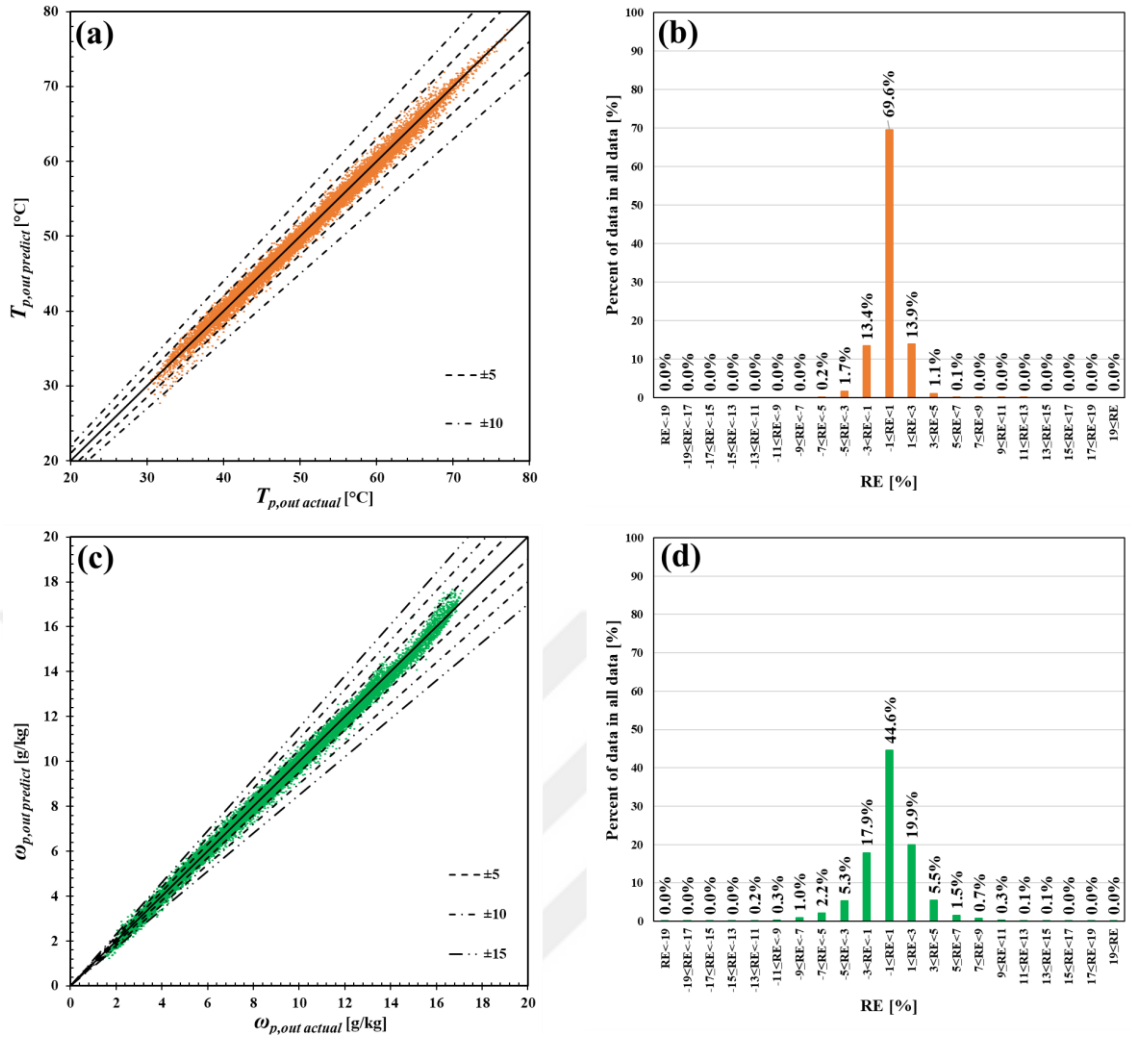


Figure 4.6. Comparison of predicted data from 3rd Degree Cross model with actual data.

The prediction data and actual data for the Response Surface model are compared in Figure 4.7. When examining Figure 4.7a, it is observed that the majority of $T_{p,out}$ data points fall within the $\pm 10\%$ error band. The number of $T_{p,out}$ data points within the $\pm 3\%$ error range for the Response Surface model is 10.3% less than that for the 3rd Degree Cross model. The same performance reduction is observed for $\omega_{p,out}$ as well. The number of $\omega_{p,out}$ data points within the $\pm 3\%$ error range for the response surface model is 24.2% less than that for the 3rd Degree Cross model.

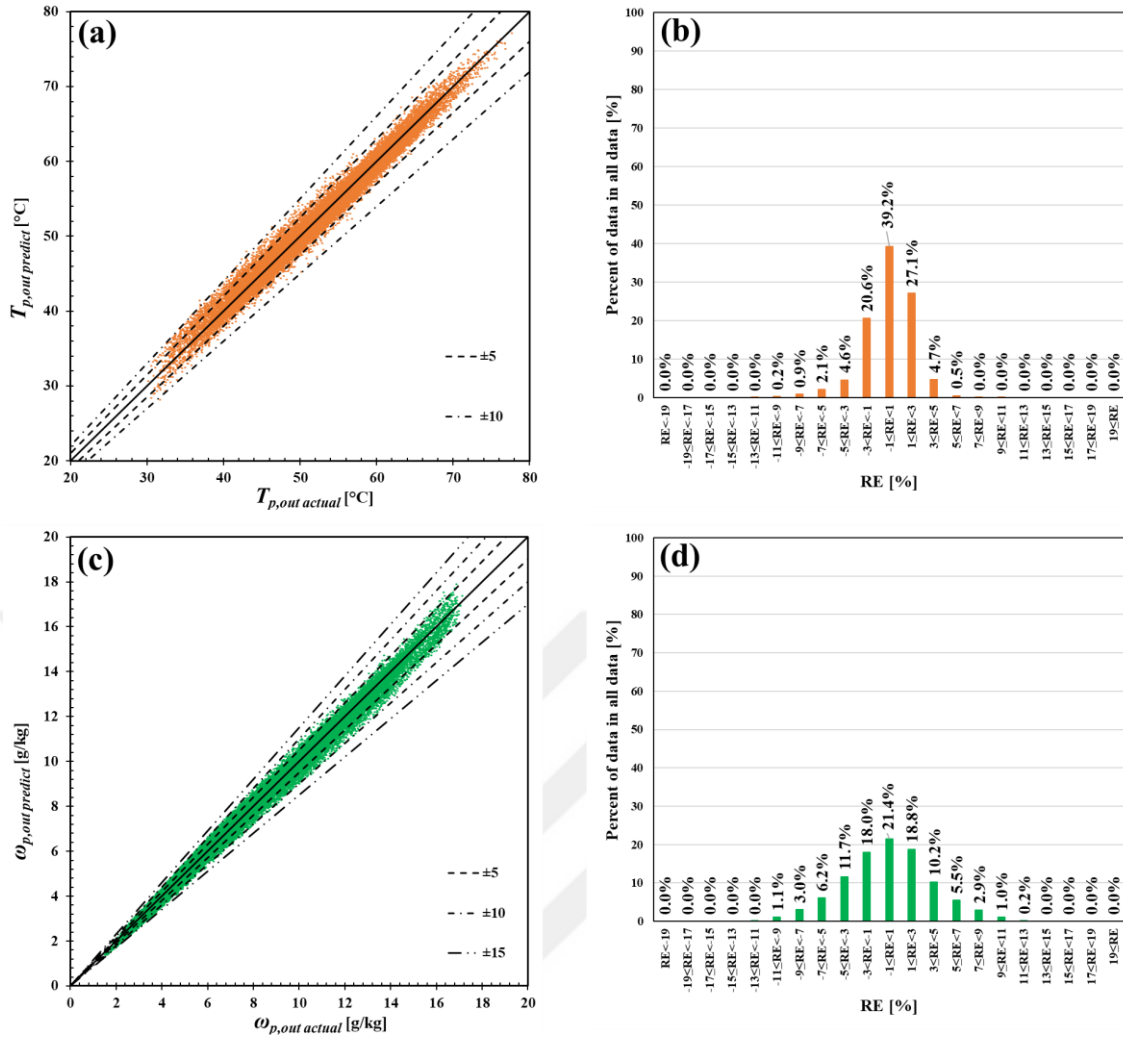


Figure 4.7. Comparison of predicted data from Response Surface model with actual data.

Table 4.9 is a comprehensive statistical summary of the graphs presented in Figures 4.1 to 4.7. It shows the percentage of data points, among 32,975 data points, predicted by a model with less than $\pm 5\%$, $\pm 10\%$, $\pm 15\%$, and $\pm 20\%$ error, along with the maximum error. When the models are compared with their cross-term versions, it is observed that the maximum error rate decreases and both $T_{p,out}$ and $\omega_{p,out}$ data is predicted within lower error ranges.

Additionally, there is a similar improvement trend as the polynomial degree of the MLR models increases. Based on the comparison using Table 4.9, it is observed that the 3rd Degree Cross model predicts the majority of the data within a low error band. On the other hand, the Response Surface model, which is highlighted in Table 4.9 for its fewer coefficients and ease of use, also predicts within low error ranges. For temperature prediction, the maximum relative error for the 3rd Degree Cross model is 12.21%, while it is 12.65% for the Response Surface model. For humidity ratio, the maximum relative error is 31.42% for the 3rd Degree Cross model, while it is 12.19% for the Response Surface model.

Table 4.9. Data distribution in percentage error for Multiple Linear Regression models.

Model	Temperature					Humidity ratio				
	± 5	± 10	± 15	± 20	Max. Error (%)	± 5	± 10	± 15	± 20	Max. Error (%)
1 st Degree	78.20	94.69	98.38	99.66	29.50	43.86	75.91	91.09	95.72	141.03
1 st Degree Cross	88.67	98.09	99.77	99.99	21.69	59.66	90.73	98.14	99.36	49.10
2 nd Degree	88.94	97.52	99.44	99.94	23.67	58.14	83.55	92.98	96.82	97.44
2 nd Degree Cross	98.41	100.00	100.00	100.00	9.46	87.31	98.73	99.92	99.99	23.11
3 rd Degree	90.25	97.89	99.53	99.95	24.18	61.56	84.98	93.11	96.83	96.48
3rd Degree Cross	99.63	99.99	100.00	100.00	12.21	93.30	99.14	99.86	99.96	31.43
Response Surface	96.22	99.94	100.00	100.00	12.65	80.09	99.20	100.00	100.00	12.19

When these figures and tables are compared among themselves and in general, it is concluded that more accurate prediction values are achieved as the polynomial degree increases and cross terms are added. Moreover, it is observed that as the complexity of the model increases, i.e., as the polynomial degree and cross terms are added, the maximum error range decreases.

4.2. Comparison of Decision Tree models

45 Decision Tree models were developed using random forest (RF), adaptive boosting (AB), and random tree (RT) methods. These models were first compared within their respective groups, and then the best models from these three groups were compared with each other (Table 4.10). The following conclusions were reached.

Random Forest:

- The performance of the random forest models increases as the maximum number of splits increases.
- When the maximum number of splits is kept constant, the performance of the model improves with an increase in the number of trees.
- Generally, curvature and interaction-curvature predictors provide better results compared to the allsplit predictor.
- Among the developed Random Forest models, the DT-18 model made the best prediction.

Adaptive Boosting:

- As the maximum number of splits increases, a decrease in model performance is observed.
- The allsplit predictor provides better predictions for adaptive boosting models compared to other predictors.
- Among the obtained adaptive boosting models, the DT-28 model yielded the best result.

Random Tree:

- An increase in the number of maximum splits improves the performance of the random tree models.
- There is no clear preference in predictor selection. Among models with 700 splits, the DT-43 model with the allsplit predictor yields good results, while among models with 500 splits, the DT-38 model with the curvature predictor performs better compared to others (DT-37, DT-39).
- Among the developed random tree models, the DT-43 model yielded the best result.



Table 4.10. Comparison of decision tree models.

Model	Tree	Max. Tree	Max. Split	Predictor	RMSE		R ²	
					$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	$T_{p,out}$	$\omega_{p,out}$
DT-1	RF	500	500	allsplits	1.618116	0.444410	0.952424	0.982059
DT-2	RF	500	500	curvature	1.616137	0.440454	0.952539	0.982372
DT-3	RF	500	500	int.curvature	1.595055	0.441135	0.953770	0.982324
DT-4	RF	500	600	allsplits	1.526892	0.421426	0.957637	0.983867
DT-5	RF	500	600	curvature	1.524008	0.423320	0.957796	0.983718
DT-6	RF	500	600	int.curvature	1.521447	0.427083	0.957938	0.983432
DT-7	RF	500	700	allsplits	1.496462	0.413763	0.959309	0.984444
DT-8	RF	500	700	curvature	1.476550	0.408656	0.960384	0.984833
DT-9	RF	500	700	int.curvature	1.483442	0.407063	0.960014	0.984946
DT-10	RF	1000	500	allsplits	1.613939	0.444522	0.952669	0.982050
DT-11	RF	1000	500	curvature	1.591948	0.440227	0.953950	0.982393
DT-12	RF	1000	500	int.curvature	1.590314	0.438976	0.954045	0.982494
DT-13	RF	1000	600	allsplits	1.524434	0.419047	0.957773	0.984046
DT-14	RF	1000	600	curvature	1.520362	0.424735	0.957999	0.983607
DT-15	RF	1000	600	int.curvature	1.520691	0.426146	0.957980	0.983500
DT-16	RF	1000	700	allsplits	1.497999	0.412311	0.959225	0.984553
DT-17	RF	1000	700	curvature	1.482498	0.408534	0.960065	0.984841
DT-18	RF	1000	700	int.curvature	1.476448	0.407799	0.960390	0.984889
DT-19	AB	500	500	allsplits	0.743303	0.204939	0.997487	0.999045
DT-20	AB	500	500	curvature	1.173882	0.320780	0.983166	0.993884
DT-21	AB	500	500	int.curvature	1.097133	0.280713	0.987607	0.995567
DT-22	AB	500	600	allsplits	0.816149	0.207846	0.996973	0.999018
DT-23	AB	500	600	curvature	1.302498	0.323728	0.978123	0.993847
DT-24	AB	500	600	int.curvature	1.188529	0.284781	0.984259	0.995520
DT-25	AB	500	700	allsplits	0.882496	0.202237	0.996462	0.999072
DT-26	AB	500	700	curvature	1.348703	0.329242	0.976603	0.993306
DT-27	AB	500	700	int.curvature	1.114899	0.269444	0.986926	0.996611
DT-28	AB	1000	500	allsplits	0.710634	0.190263	0.997706	0.999177
DT-29	AB	1000	500	curvature	1.155076	0.311929	0.984226	0.993919
DT-30	AB	1000	500	int.curvature	1.131592	0.294279	0.984808	0.995807
DT-31	AB	1000	600	allsplits	0.803679	0.198242	0.997066	0.999107
DT-32	AB	1000	600	curvature	1.274480	0.338674	0.978891	0.993210
DT-33	AB	1000	600	int.curvature	1.183976	0.277128	0.984779	0.996299
DT-34	AB	1000	700	allsplits	0.846581	0.217025	0.996744	0.998931
DT-35	AB	1000	700	curvature	1.197122	0.327567	0.983063	0.993508
DT-36	AB	1000	700	int.curvature	1.109414	0.283019	0.988341	0.996205
DT-37	RT	1	500	allsplits	2.330429	0.605392	0.912502	0.969381
DT-38	RT	1	500	curvature	2.258097	0.613759	0.911631	0.968245
DT-39	RT	1	500	int.curvature	2.335037	0.620403	0.908993	0.968194
DT-40	RT	1	600	allsplits	2.183117	0.581292	0.922842	0.972353
DT-41	RT	1	600	curvature	2.164532	0.586686	0.924086	0.972202
DT-42	RT	1	600	int.curvature	2.211628	0.572626	0.921229	0.973045
DT-43	RT	1	700	allsplits	2.125629	0.572626	0.928372	0.973733
DT-44	RT	1	700	curvature	2.144551	0.588473	0.927272	0.972694
DT-45	RT	1	700	int.curvature	2.188173	0.580775	0.922143	0.972732

According to Table 4.10, Figures 4.8 to 4.10 present the best random forest model (DT-18), the best adaptive boosting model (DT-28), and the best random tree model (DT-43).

In Figure 4.8a, the DT-18 model has provided results for $T_{p,out}$ within the $\pm 15\%$ error band. However, it is observed that the DT-18 model falls outside the $\pm 15\%$ error band for $\omega_{p,out}$ in low humidity regions, particularly below 6 g/kg (Figure 4.8c).

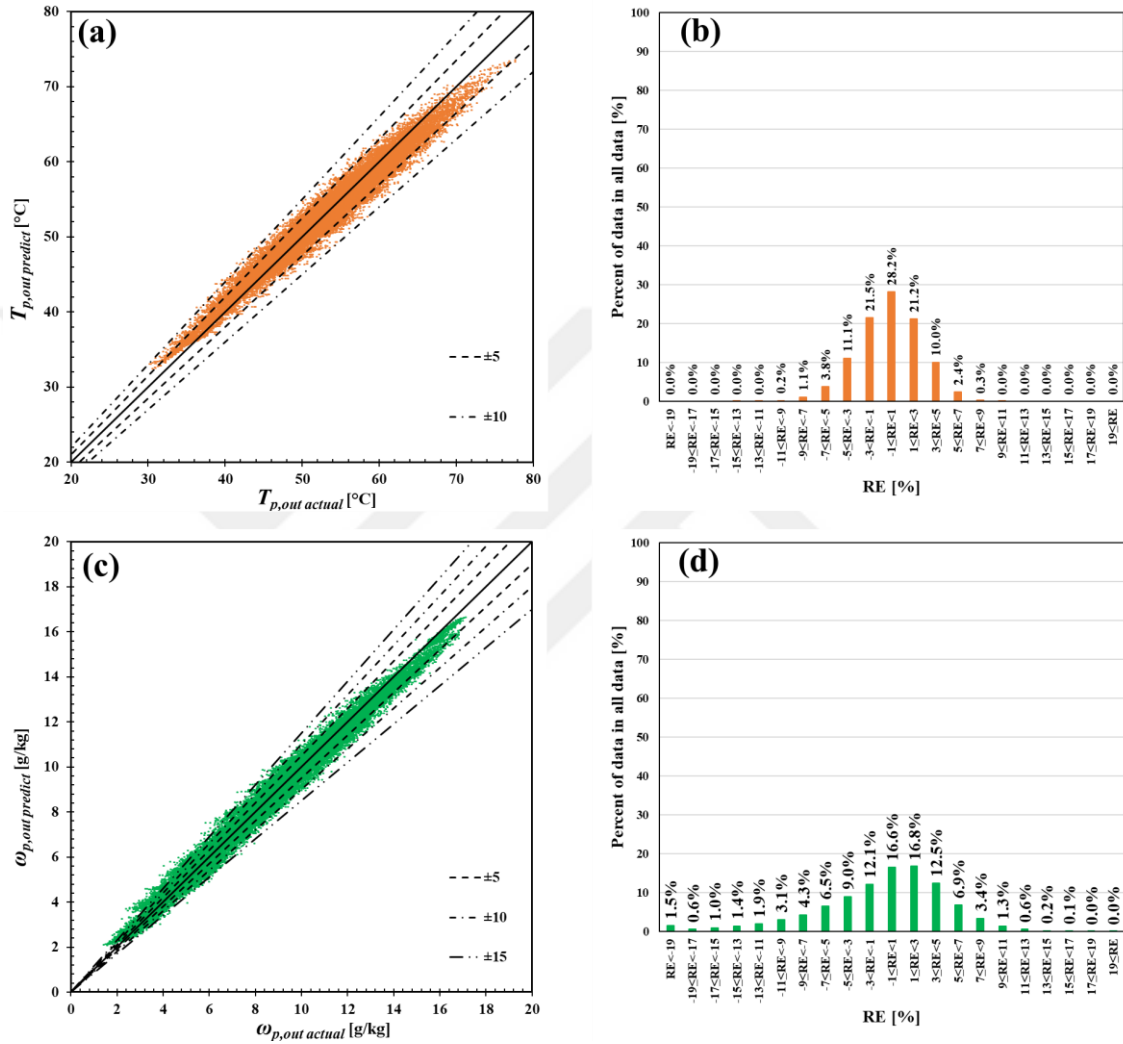


Figure 4.8. Comparison of predicted data from DT-18 model with actual data.

When comparing Figure 4.9a with Figure 4.8a, it can be observed that the $T_{p,out}$ data for the DT-28 model falls within the $\pm 10\%$ error band compared to the DT-18 model. Additionally, according to Figure 4.9b, 98.9% of the generated data is within a $\pm 3\%$ error range, and this value is 95.9% for $\omega_{p,out}$ (Figure 4.9d). The DT-28 model also provides more accurate results in low humidity regions compared to the DT-18 model (Figure 4.9c).

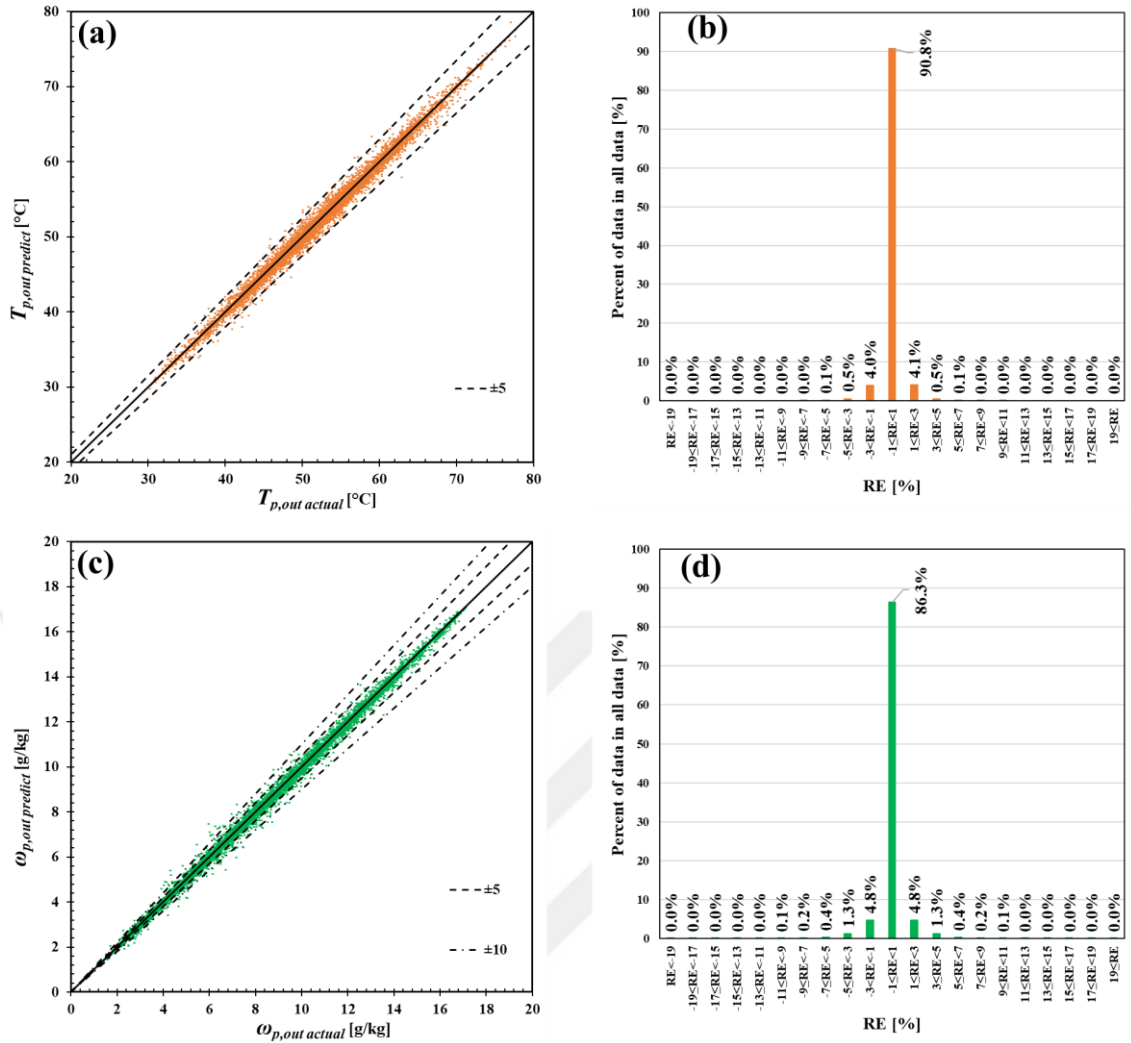


Figure 4.9. Comparison of predicted data from DT-28 model with actual data.

As shown in Figure 4.10, the DT-43 model predicts with much higher error margins compared to the developed DT-18 and DT-28 models (Figures 4.10a and 4.10c). For $T_{p,out}$, 59.5% of the data produced by the model falls within the $\pm 3\%$ range. For $\omega_{p,out}$, 39% of the data is predicted within this range.

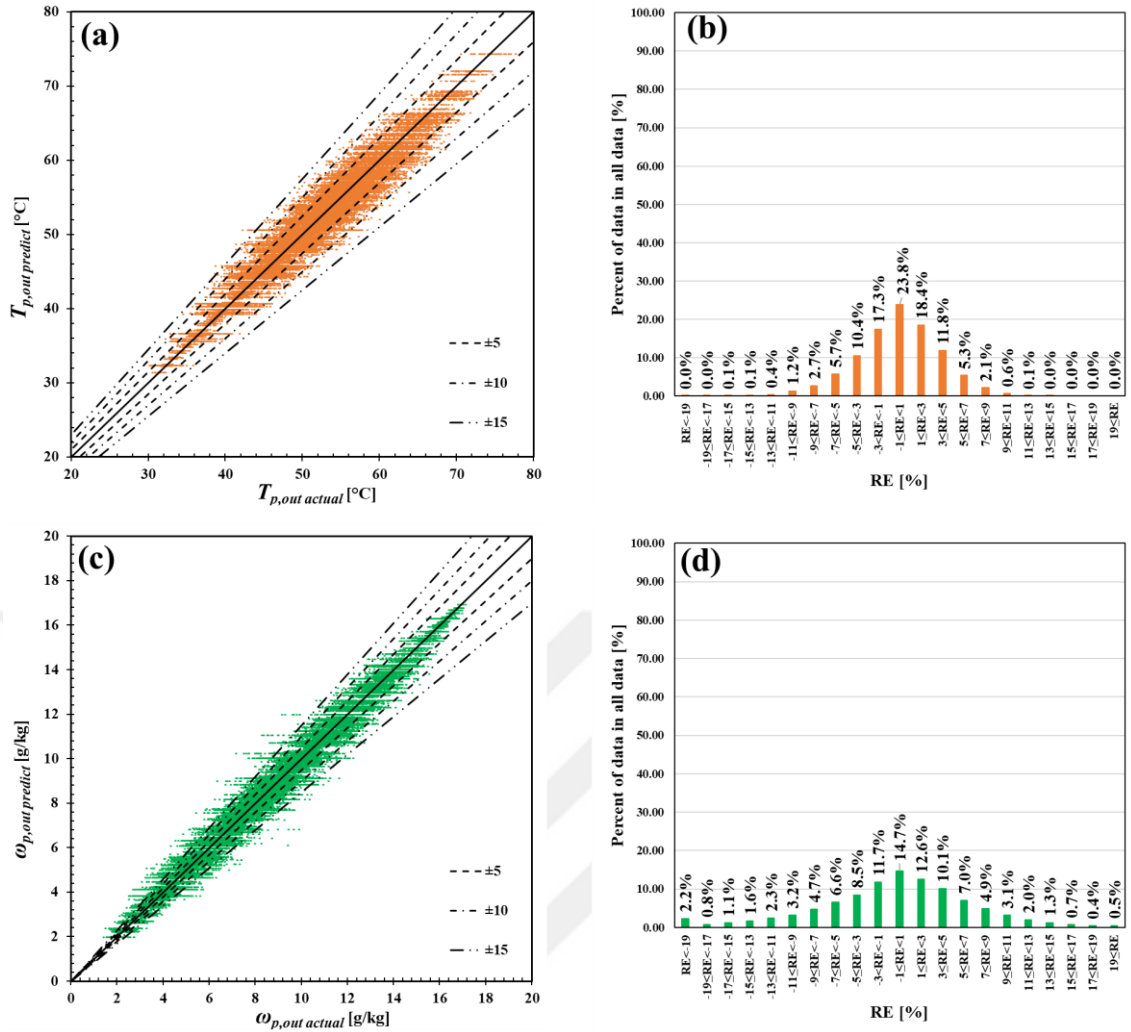


Figure 4.10. Comparison of predicted data from DT-43 model with actual data.

From Table 4.11, the following conclusions have been reached:

- Among the models, the random forest model exhibits higher prediction performance within the $\pm 5\%$ error range compared to the random tree model, but lower performance compared to the adaptive boosting method.
- The DT-28 model has the lowest relative error values for $T_{p,out}$ and $\omega_{p,out}$ compared to the other models, with these values being 9.55% and 26.76%, respectively.

Based on a comprehensive comparison considering RMSE, R^2 , and maximum relative error, the decision tree model DT-28 is the most accurate in making predictions.

Table 4.11. Data distribution in percentage error for Decision tree models.

Model	Temperature					Humidity ratio				
	±5	±10	±15	±20	Max. Error	±5	±10	±15	±20	Max. Error
DT-1	89.09	99.74	100.00	100.00	14.12	63.71	88.57	96.12	98.44	61.94
DT-2	89.12	99.73	100.00	100.00	14.14	63.68	88.72	95.91	98.27	61.33
DT-3	89.52	99.77	100.00	100.00	13.99	63.50	88.78	95.89	98.31	60.74
DT-4	90.97	99.85	100.00	100.00	13.51	66.30	90.07	96.70	98.74	57.38
DT-5	91.00	99.83	100.00	100.00	13.83	65.57	89.88	96.40	98.54	57.54
DT-6	91.13	99.85	100.00	100.00	13.42	65.13	89.72	96.44	98.53	58.60
DT-7	91.65	99.87	100.00	100.00	13.19	67.09	90.63	97.01	98.88	56.64
DT-8	91.96	99.89	100.00	100.00	13.12	66.93	90.64	96.76	98.70	58.13
DT-9	91.92	99.88	100.00	100.00	13.20	67.23	90.59	96.75	98.71	56.19
DT-10	89.22	99.73	100.00	100.00	14.11	63.63	88.63	96.12	98.41	62.06
DT-11	89.64	99.77	100.00	100.00	14.21	63.83	88.82	95.97	98.30	61.94
DT-12	89.52	99.75	100.00	100.00	13.94	63.80	88.91	95.92	98.28	61.78
DT-13	91.08	99.83	100.00	100.00	13.97	66.34	90.23	96.79	98.74	58.12
DT-14	91.14	99.85	100.00	100.00	13.57	65.32	89.87	96.44	98.56	58.77
DT-15	91.10	99.84	100.00	100.00	13.93	65.19	89.86	96.43	98.54	59.75
DT-16	91.61	99.87	100.00	100.00	13.56	67.19	90.68	97.03	98.85	56.02
DT-17	91.93	99.89	100.00	100.00	13.37	67.03	90.66	96.80	98.74	57.84
DT-18	92.06	99.88	100.00	100.00	13.12	67.04	90.70	96.77	98.75	57.40
DT-19	99.76	100.00	100.00	100.00	11.92	98.35	99.74	99.94	99.98	37.44
DT-20	98.07	99.95	99.99	100.00	17.31	86.32	98.01	99.63	99.92	32.61
DT-21	99.06	99.94	99.99	99.99	26.02	90.74	99.02	99.86	99.96	35.29
DT-22	99.64	99.97	100.00	100.00	14.09	98.12	99.72	99.92	99.97	35.05
DT-23	97.16	99.92	100.00	100.00	14.69	86.18	98.05	99.59	99.88	36.49
DT-24	98.51	99.96	100.00	100.00	20.13	90.01	98.73	99.77	99.95	32.67
DT-25	99.59	99.98	100.00	100.00	13.25	98.09	99.73	99.92	99.98	39.47
DT-26	96.73	99.91	100.00	100.00	16.49	84.79	97.44	99.46	99.86	38.93
DT-27	98.84	99.95	100.00	100.00	17.48	93.25	99.09	99.86	99.96	47.18
DT-28	99.84	100.00	100.00	100.00	9.55	98.53	99.75	99.92	99.98	26.76
DT-29	98.37	99.97	99.99	100.00	16.43	86.06	97.78	99.57	99.89	36.17
DT-30	98.49	99.97	100.00	100.00	12.71	91.28	98.81	99.78	99.96	51.31
DT-31	99.71	99.98	100.00	100.00	22.83	98.28	99.72	99.95	99.98	31.94
DT-32	97.21	99.97	100.00	100.00	17.26	84.58	97.35	99.47	99.91	42.40
DT-33	98.61	99.96	100.00	100.00	16.82	92.85	99.10	99.78	99.91	31.83
DT-34	99.66	100.00	100.00	100.00	20.49	97.97	99.68	99.91	99.97	36.69
DT-35	98.05	99.94	100.00	100.00	13.52	85.88	97.87	99.55	99.88	43.47
DT-36	99.06	99.97	100.00	100.00	15.57	92.25	99.01	99.74	99.93	44.36
DT-37	77.56	97.76	99.85	99.99	28.14	53.65	81.06	92.55	96.96	55.77
DT-38	76.87	97.81	99.91	99.99	20.55	52.84	80.79	92.52	96.86	57.27
DT-39	76.19	97.45	99.83	99.99	24.10	52.76	80.71	92.49	96.85	65.68
DT-40	79.95	98.48	99.95	100.00	19.10	56.28	83.09	93.74	97.40	71.52
DT-41	80.05	98.57	99.96	99.99	22.92	55.85	82.70	93.54	97.43	70.10
DT-42	79.24	98.40	99.92	99.99	22.24	56.01	82.84	93.60	97.52	55.53
DT-43	81.72	98.62	99.93	100.00	19.97	57.61	84.29	94.28	97.75	62.32
DT-44	81.29	98.77	99.92	100.00	17.75	56.71	83.70	93.93	97.70	67.55
DT-45	80.20	98.64	99.93	100.00	34.16	56.53	83.38	93.87	97.74	77.13

4.3. Comparison of Support Vector Machine Regression Models

The SVM models vary according to the kernel function, polynomial degrees, box constraint, and solver. These features are factors that directly affect the performance of the models. In this context, 12 SVM regression models were developed and their performances were examined in Table 4.12. Accordingly, the following general conclusions were reached.

- Kernel function: Models with Gaussian and RBF kernel functions generally exhibit higher accuracy.
- Solver: When comparing the performance of models using SMO and ISDA solvers, generally similar results are obtained.
- Polynomial degree: As the polynomial degree increases, an improvement in model performance is observed.

Among the SVM models, SVM-4 and SVM-5 stand out as the models with the highest accuracy for both $T_{p,out}$ and $\omega_{p,out}$. Particularly, the SVM-5 model provides the most accurate results when considering both RMSE and R^2 values.

Among the developed SVM models, the SVM-5 model has the lowest RMSE (0.378021 °C) and the highest R^2 (0.997404) values for $T_{p,out}$. For $\omega_{p,out}$, it has an RMSE of 0.10817 g/kg and an R^2 value of 0.99894.

Table 4.12. Comparison of SVM regression models.

Model	Kernel Function	Degr. of Poly.	RMSE		R^2	
			$T_{p,out}$ [°C]	$\omega_{p,out}$ [g/kg]	$T_{p,out}$	$\omega_{p,out}$
SVM-1	Linear	-	2.40603	0.72581	0.89481	0.99656
SVM-2	Linear	-	2.40065	0.72491	0.89528	0.95226
SVM-3	Gaussian	-	0.41267	0.10536	0.99690	0.99899
SVM-4	Gaussian	-	0.39433	0.10863	0.99717	0.99893
SVM-5	rbf	-	0.37802	0.10817	0.99740	0.99894
SVM-6	rbf	-	0.40224	0.10536	0.99706	0.99899
SVM-7	Polynomial	1	2.40420	0.72229	0.89497	0.95261
SVM-8	Polynomial	1	2.40331	0.72526	0.89505	0.95222
SVM-9	Polynomial	2	1.13649	0.31113	0.97653	0.99121
SVM-10	Polynomial	2	1.13754	0.31064	0.97649	0.99123
SVM-11	Polynomial	3	0.63553	0.17464	0.99266	0.99723
SVM-12	Polynomial	3	0.63246	0.17833	0.99273	0.99711

Figure 4.11 shows a comparison of the data generated by the SVM-5 model with the actual data. According to Table 4.12, the SVM-5 model, which provides the best results, has 99.8% of its predicted $T_{p,out}$ data within the $\pm 5\%$ error band (Figure 4.11a). When examining Figure 4.11c, 98.6% of the data generated by the SVM-5 model for $\omega_{p,out}$ falls within the $\pm 5\%$ error band. For $T_{p,out}$, 99% of the generated data falls within the $\pm 3\%$ error range (Figure 4.11b). For $\omega_{p,out}$, 95.6% of the data falls within the $\pm 3\%$ error range (Figure 4.11d).

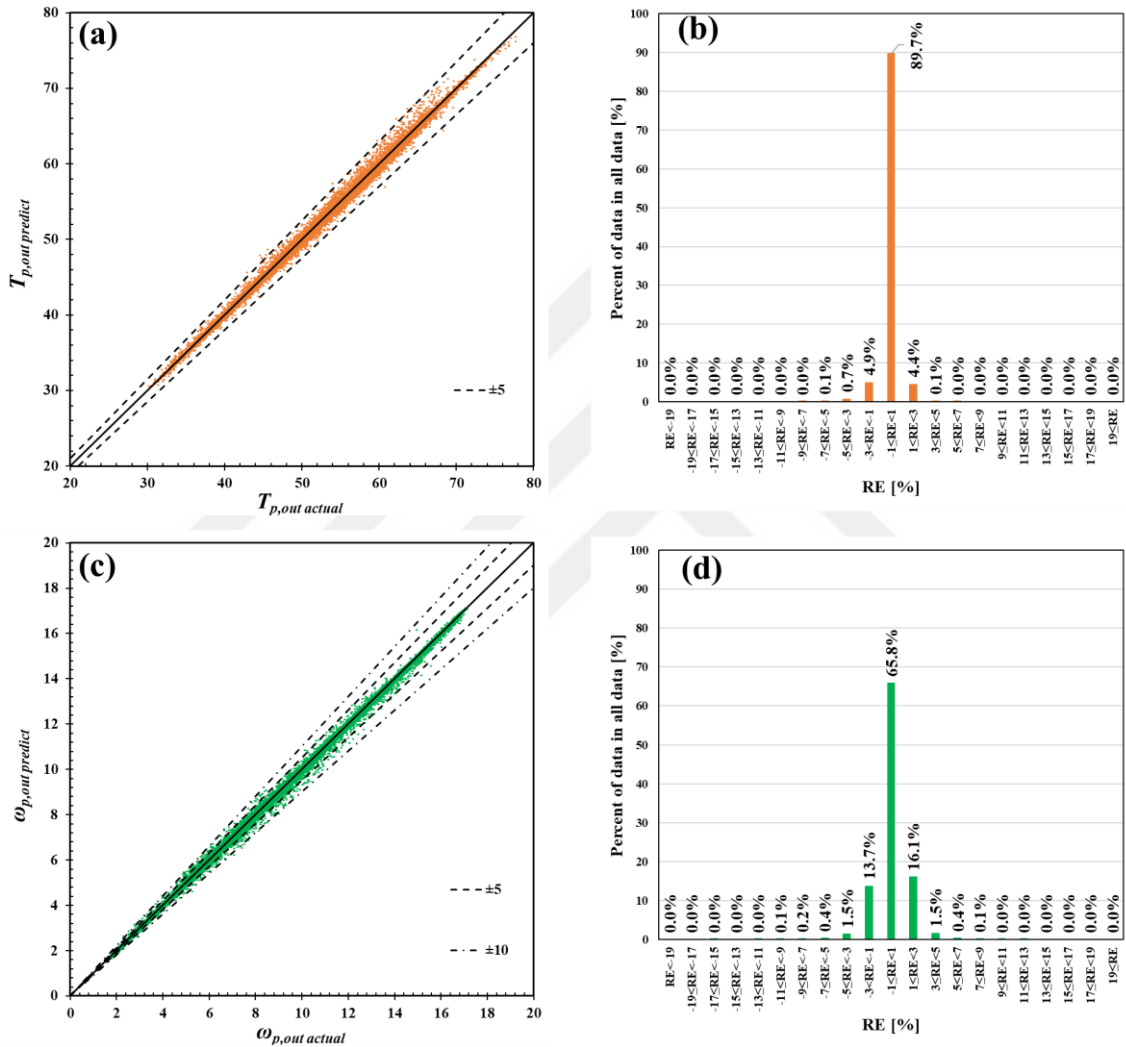


Figure 4.11. Comparison of predicted data from SVM-5 model with actual data.

When examining Figure 4.12a for the SVM-9 model with a polynomial degree of 2, it is observed that more predicted data for $T_{p,out}$ falls outside the $\pm 5\%$ error band compared to the SVM-5 model. The same trend is evident for $\omega_{p,out}$ as well (Figure 4.12c). The amount of data within the $\pm 3\%$ error range for $T_{p,out}$ has decreased by 11.7%. For $\omega_{p,out}$, the decrease is 33.6%.

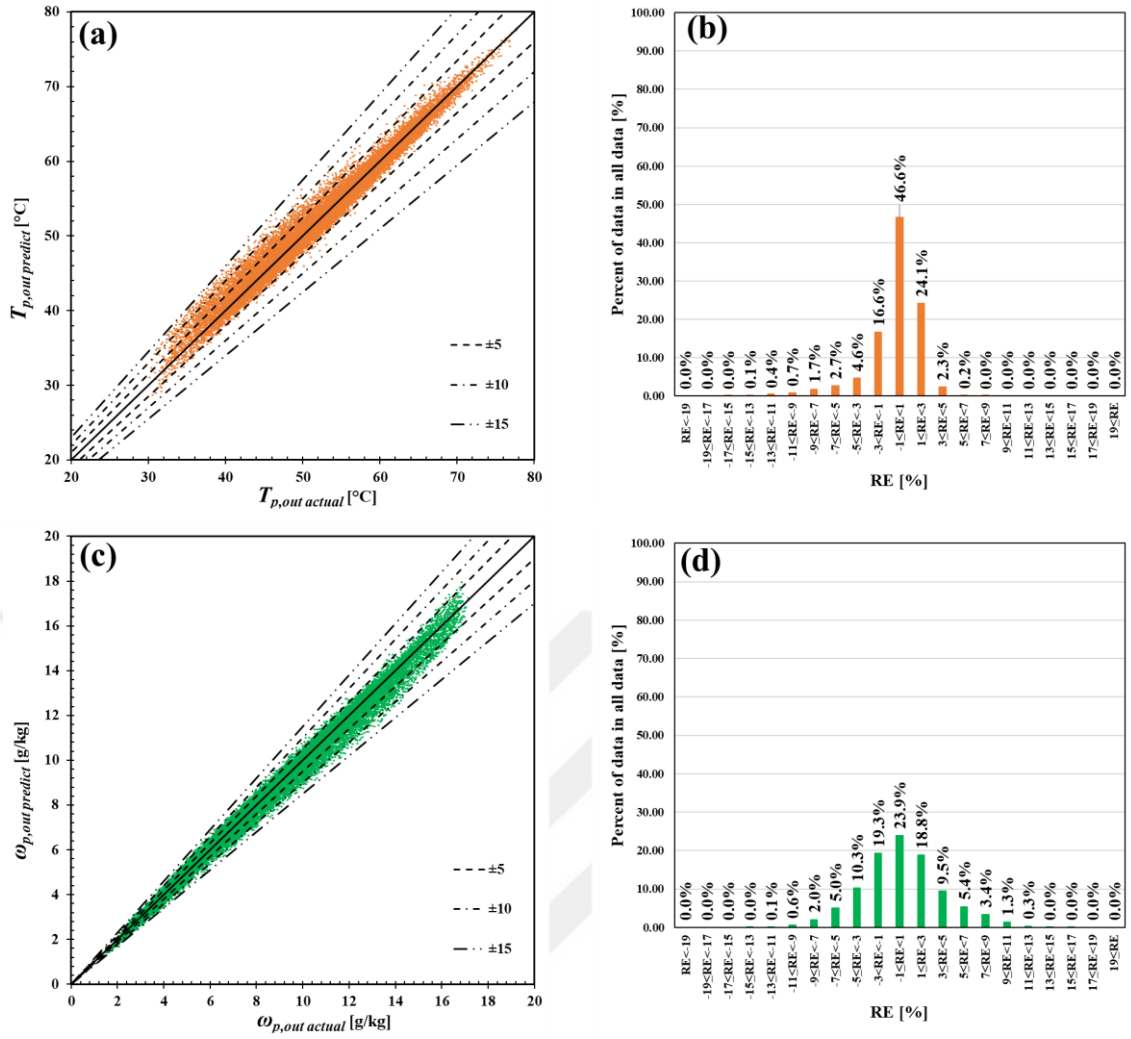


Figure 4.12. Comparison of predicted data from SVM-9 model with actual data.

According to SVM-9, with an increase in the polynomial degree, it is observed in Figure 4.13a that the predicted data ($T_{p,out}$) for SVM-12 is concentrated within the $\pm 5\%$ error band. The same trend is valid for $\omega_{p,out}$ as well (Figure 4.13c). The SVM-12 model has made significantly more predictions within the $\pm 3\%$ error range compared other SVM models developed with polynomial kernel function. Compared to the SVM-5 model, which provides the best results in terms of RMSE and R^2 values, the SVM-12 model predicted 3.3% less data within the $\pm 3\%$ error range for $T_{p,out}$ (Figure 4.13b) and 12.5% less data for $\omega_{p,out}$ (Figure 4.13d).

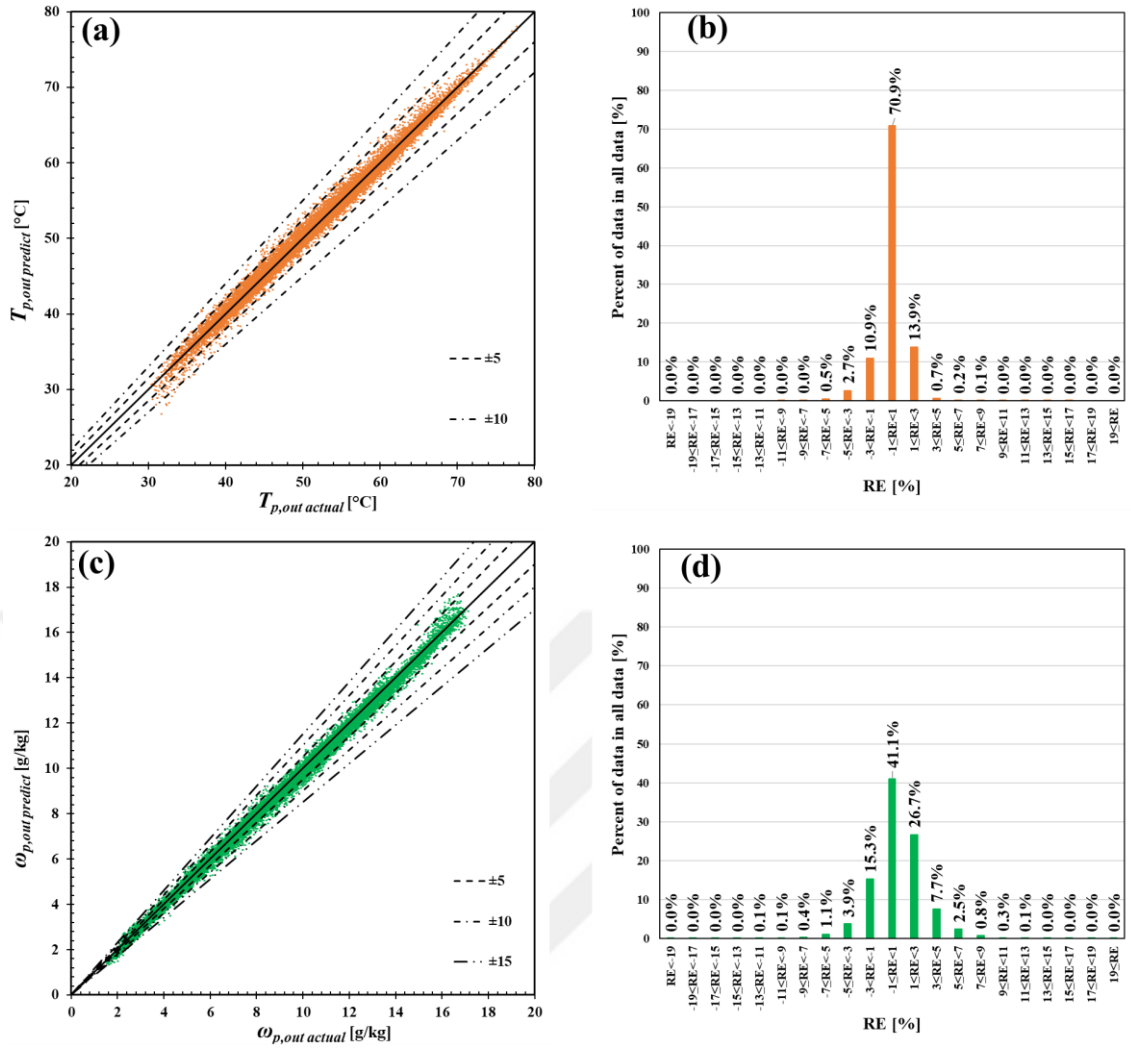


Figure 4.13. Comparison of predicted data from SVM-12 model with actual data.

Table 4.13. Distribution in percentage error for SVM regression models.

Model	Temperature					Humidity ratio				
	±5	±10	±15	±20	Max. Error	±5	±10	±15	±20	Max. Error
SVM-1	79.56	92.81	96.92	98.94	33.59	49.36	78.55	90.92	95.48	138.68
SVM-2	79.51	92.88	96.97	98.97	33.39	49.45	78.53	90.88	95.48	139.74
SVM-3	99.88	100.00	100.00	100.00	7.83	98.74	99.92	99.99	100.00	16.19
SVM-4	99.90	100.00	100.00	100.00	7.30	98.72	99.91	99.99	100.00	16.06
SVM-5	99.92	100.00	100.00	100.00	7.67	98.67	99.90	99.99	100.00	16.42
SVM-6	99.90	100.00	100.00	100.00	7.27	98.78	99.92	99.99	100.00	15.95
SVM-7	79.50	92.78	96.94	98.95	33.39	49.19	78.59	90.89	95.40	140.27
SVM-8	79.51	92.82	96.93	98.95	33.33	49.46	78.63	90.79	95.40	140.06
SVM-9	94.20	99.18	99.99	100.00	16.42	81.84	98.88	99.99	100.00	16.65
SVM-10	94.19	99.17	99.99	100.00	16.32	81.78	98.87	99.99	100.00	16.39
SVM-11	99.09	99.97	100.00	100.00	15.02	95.03	99.61	99.92	99.99	20.88
SVM-12	99.16	99.97	100.00	100.00	15.24	94.56	99.53	99.90	99.99	23.62

According to Table 4.13, the Linear Kernel function and first degree polynomial kernel function provide poorer results for $T_{p,out}$ and $\omega_{p,out}$ predictions compared to other models. Based on the comparison between. It has been observed that increasing the polynomial degree improves the model's performance in terms of maximum error and predictions within the lower error band. Although the SVM-5 model provides the best results in terms of RMSE and R^2 (Table 4.12), the SVM-4 model stands out in terms of maximum error in Table 4.13. However, the difference between SVM-4 and SVM-5 is negligible. Therefore, based on this comparison, the SVM-5 model is identified as the best model among the SVM models.

4.4. Comparison of Multilayer Perceptron Models.

A total of 32 MLP models were developed using 4 different training functions, 2 different hidden layers, and 4 different neuron counts. The RMSE and R^2 values of the developed models are presented in Table 4.14.

For the trainlm training function, an increase in the number of layers or neurons improves the performance of the developed model. Among the models using this training function (MLP-1 to MLP-8), the MLP-8 model provides the best results.

The training function for the MLP models developed between MLP-9 and MLP-16 is trainbfg. Among these models, MLP-10, MLP-11, MLP-14, and MLP-16 predicted $T_{p,out}$ with high error. This indicates that an increase in the number of hidden layers or neurons does not proportionally improve performance for this training function. As shown in Table 4.14, the MLP-15 model, which has 2 hidden layers with 30 neurons in each layer, provided better predictions for both $T_{p,out}$ and $\omega_{p,out}$ compared to the MLP-16 model. Among the models using the trainbfg training function, the MLP-15 model, with 2 hidden layers and 30 neurons in each hidden layer, yielded the best results.

For the models developed with the trainscg training function, specifically between MLP-17 and MLP-24, an increase in the number of neurons generally led to an improvement in model performance, except for the MLP-20 model. The MLP-19 model provided better predictions for $T_{p,out}$ compared to the MLP-20 model. On the other hand, the MLP-20 model made more accurate predictions for $\omega_{p,out}$ than the MLP-19 model. Among this group of models, the MLP-24 model yielded the best results.

The training function for the models developed between MLP-25 and MLP-32 is trainoss. The MLP-29 model, with 2 hidden layers and 10 neurons, demonstrates better prediction performance for $T_{p,out}$ and $\omega_{p,out}$ compared to the MLP-30 model, which has 2 hidden layers and 20 neurons. The same situation applies to the MLP-31 and MLP-32 models; the MLP-31 model, despite having fewer neurons, performs better than the MLP-32 model. When examining the RMSE and R^2 values of these models, the MLP-31 model is observed to provide the best results.

Table 4.14. Comparison of Multilayer Perceptron models.

Model	Training Function	Layer Number	Neuron Numbers	RMSE		R ²	
				$T_{p,out}$ [°C]	$\omega_{p,out}$ [g kg ⁻¹]	$T_{p,out}$	$\omega_{p,out}$
MLP-1	trainlm	1	10	0.45177	0.12689	0.99656	0.99854
MLP-2	trainlm	1	20	0.33571	0.09644	0.99790	0.99914
MLP-3	trainlm	1	30	0.27695	0.08367	0.99869	0.99940
MLP-4	trainlm	1	40	0.26134	0.07937	0.99885	0.99948
MLP-5	trainlm	2	10/10	0.26077	0.08246	0.99879	0.99938
MLP-6	trainlm	2	20/20	0.21071	0.06557	0.99917	0.99961
MLP-7	trainlm	2	30/30	0.20174	0.06633	0.99938	0.99967
MLP-8	trainlm	2	40/40	0.20591	0.06928	0.99942	0.99970
MLP-9	trainbfg	1	10	0.45738	0.15199	0.99597	0.99798
MLP-10	trainbfg	1	20	2.19411	0.12042	0.91182	0.99859
MLP-11	trainbfg	1	30	2.20148	0.11180	0.91198	0.99887
MLP-12	trainbfg	1	40	2.30252	0.10863	0.90434	0.99899
MLP-13	trainbfg	2	10/10	0.32125	0.10296	0.99806	0.99903
MLP-14	trainbfg	2	20/20	2.74195	0.08718	0.86649	0.99928
MLP-15	trainbfg	2	30/30	0.25020	0.07616	0.99893	0.99949
MLP-16	trainbfg	2	40/40	2.34246	0.08544	0.90128	0.99936
MLP-17	trainscg	1	10	0.61733	0.16733	0.99308	0.99746
MLP-18	trainscg	1	20	0.60042	0.18815	0.99366	0.99694
MLP-19	trainscg	1	30	0.51807	0.18708	0.99518	0.99682
MLP-20	trainscg	1	40	0.55669	0.16664	0.99437	0.99748
MLP-21	trainscg	2	10/10	0.86441	0.12767	0.98654	0.99852
MLP-22	trainscg	2	20/20	0.69936	0.11533	0.99111	0.99879
MLP-23	trainscg	2	30/30	0.67186	0.13153	0.99198	0.99843
MLP-24	trainscg	2	40/40	0.36647	0.10724	0.99756	0.99896
MLP-25	trainoss	1	10	1.21107	0.37947	0.97303	0.98745
MLP-26	trainoss	1	20	1.15048	0.27785	0.97595	0.99290
MLP-27	trainoss	1	30	0.90216	0.21119	0.98521	0.99595
MLP-28	trainoss	1	40	0.86879	0.18841	0.98606	0.99677
MLP-29	trainoss	2	10/10	0.55991	0.20000	0.99435	0.99637
MLP-30	trainoss	2	20/20	1.14516	0.43012	0.97589	0.98320
MLP-31	trainoss	2	30/30	0.57385	0.13638	0.99402	0.99831
MLP-32	trainoss	2	40/40	0.91258	0.16852	0.98550	0.99742

In Table 4.14, the $T_{p,out}$ and $\omega_{p,out}$ data generated by the MLP-8 model, which provided the best results, are compared with the actual data (Figure 4.14a-Figure 4.14d). The data produced by the model is concentrated within a very narrow error range. As shown in Figure 4.14a, all of the $T_{p,out}$ data generated by the model falls within the $\pm 5\%$ error band. As seen in Figure 4.14b and Figure 4.14d, 99.9% of the $T_{p,out}$ data and 98.7% of the $\omega_{p,out}$ data generated by the MLP-8 model fall within the $\pm 3\%$ error range

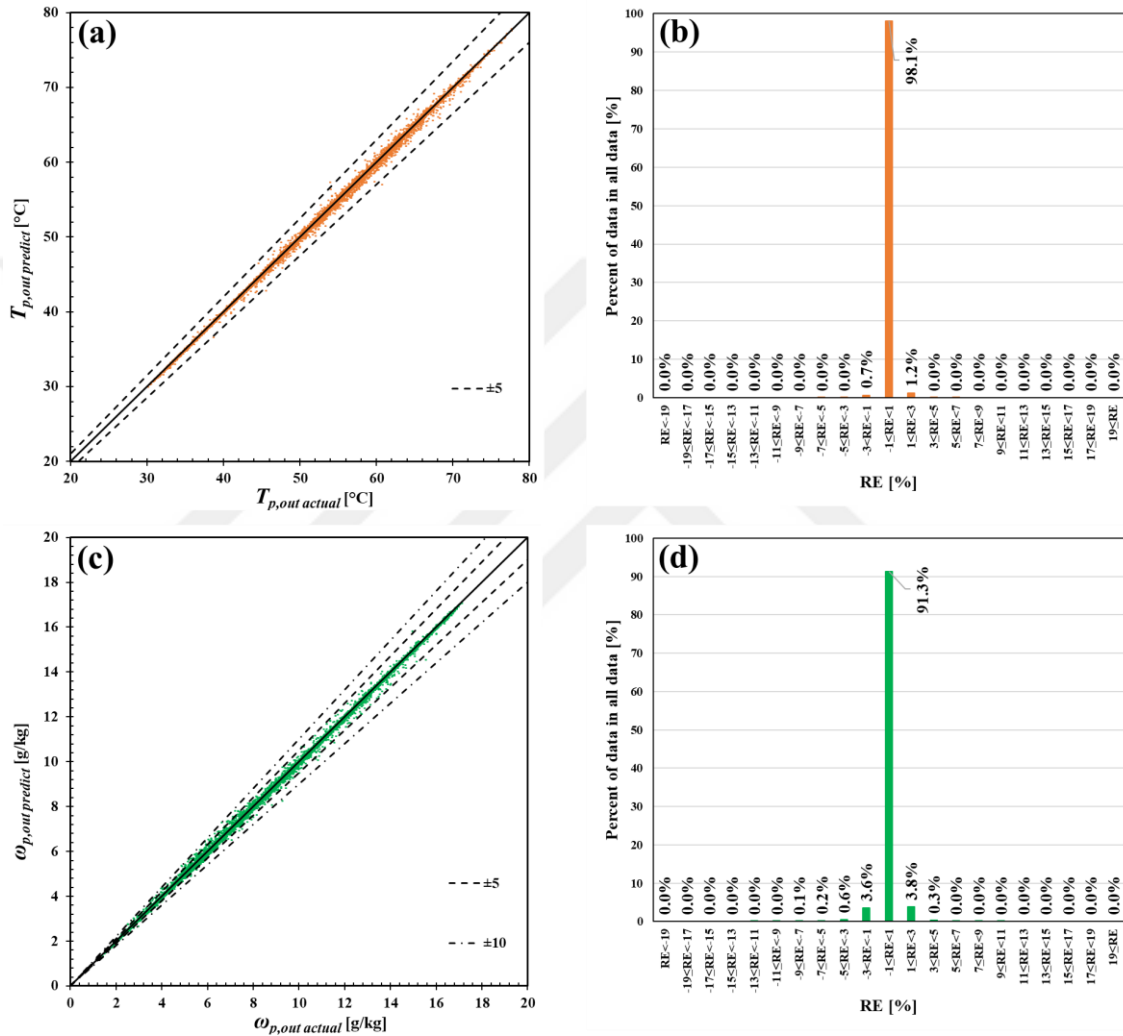


Figure 4.14. Comparison of predicted data from MLP-8 model with actual data.

The data generated by the MLP-15 model for $T_{p,out}$ (Figure 4.15a) and $\omega_{p,out}$ (Figure 4.15c) are compared with the actual values. Additionally, the relative errors of the data produced by this model are provided in Figure 4.15b and Figure 4.15d. When comparing the MLP-15 model (Figure 4.9) with the MLP-8 model (Figure 4.8), it is observed that the number of data points for $T_{p,out}$ within the $\pm 1\%$ error band (Figure 4.15b) is 1.7% less for the MLP-15 model compared to the MLP-8 model (Figure 4.14b). The same reduction is observed for $\omega_{p,out}$ (Figure 4.14b-Figure 4.15b).

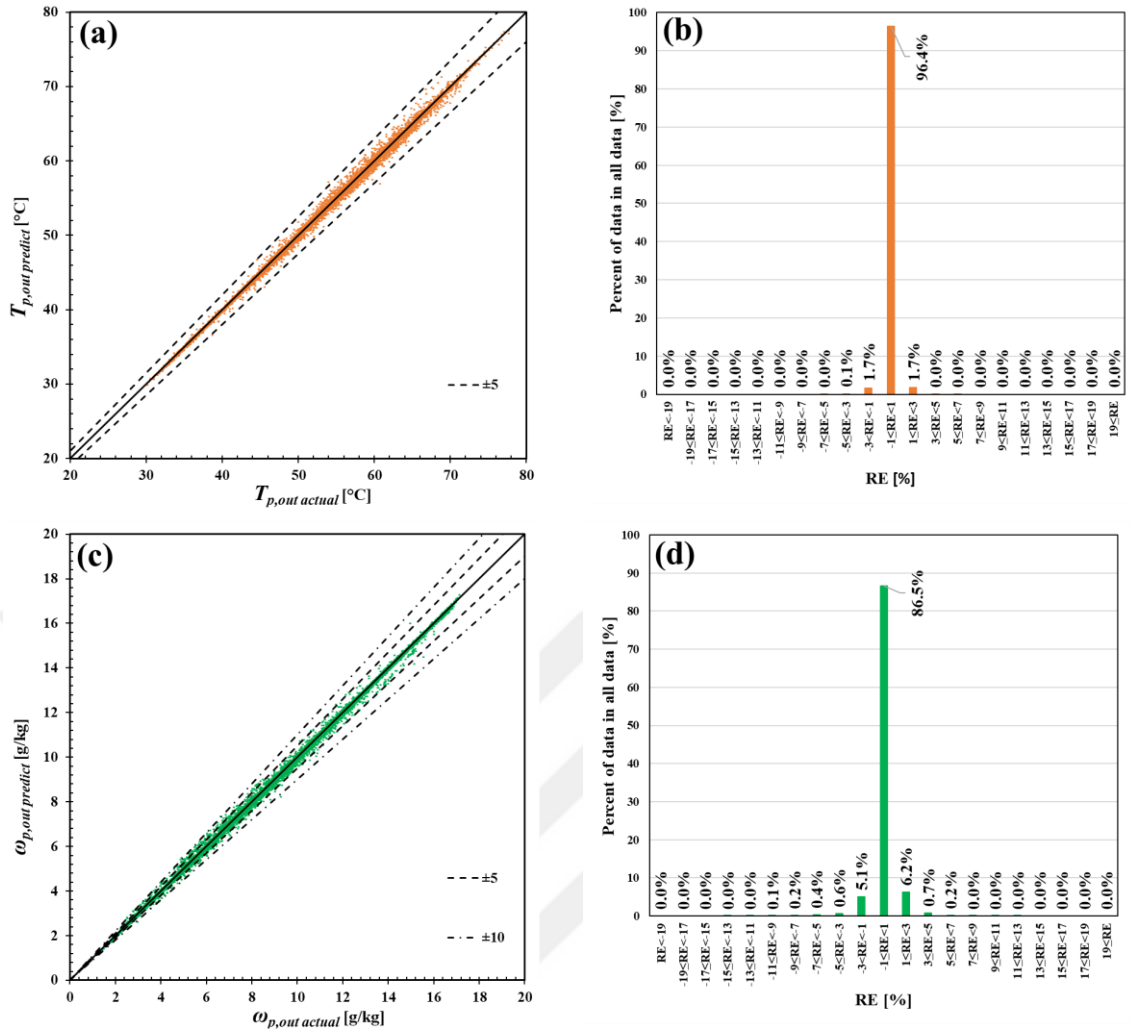


Figure 4.15. Comparison of predicted data from MLP-15 model with actual data.

The $T_{p,out}$ data predicted by the MLP-24 model shows a tendency to deviate from the center towards the $\pm 5\%$ error band compared to the previous two models (MLP-8 and MLP-15). The model's lower performance is also evident in Figure 4.16b. The number of data points within the $\pm 1\%$ error range is 9.2% less compared to the MLP-8 model (Figure 4.14b). The same trend is observed for $\omega_{p,out}$, with a reduction of 24.2%.

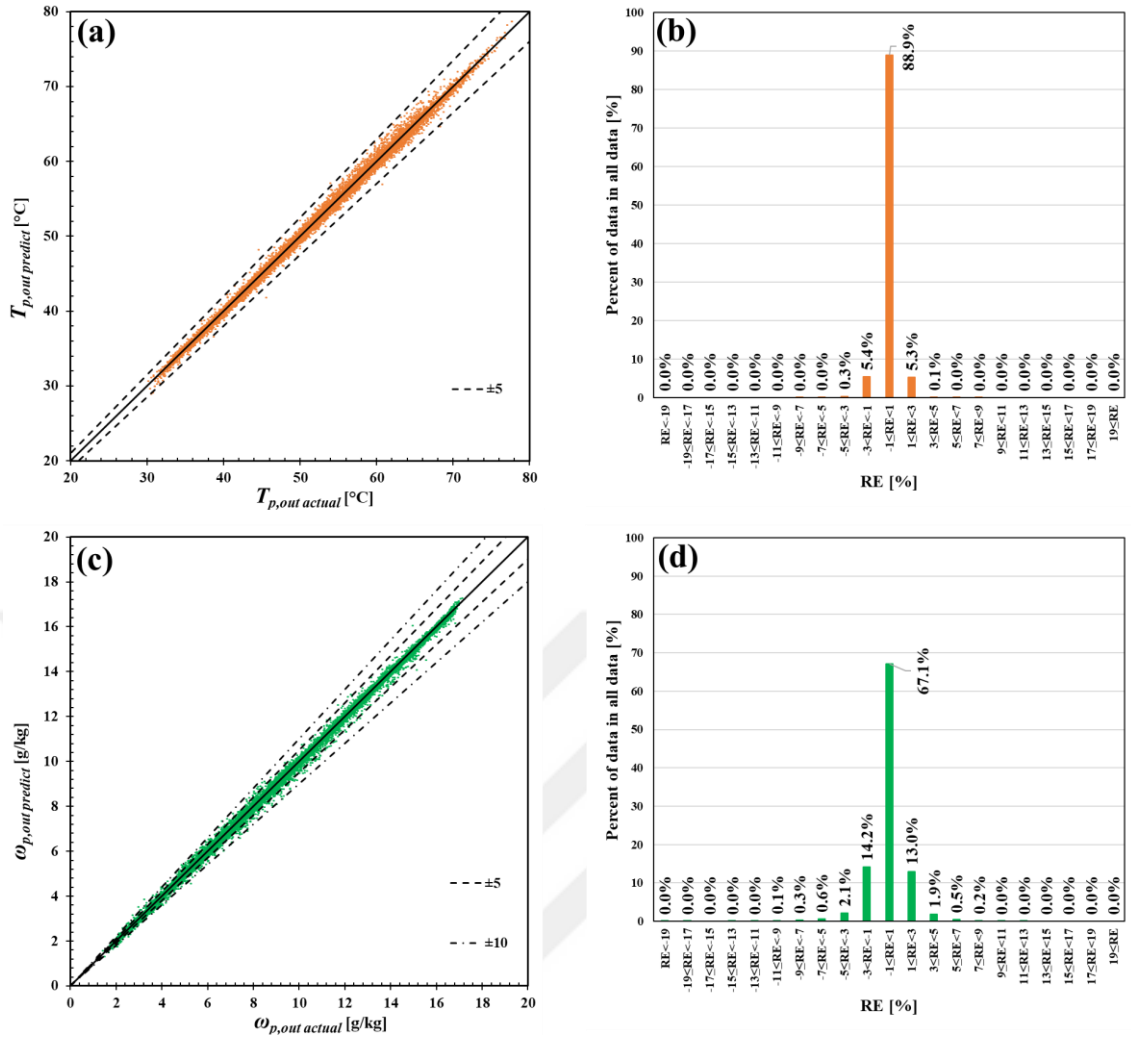


Figure 4.16. Comparison of predicted data from MLP-24 model with actual data.

The predicted $T_{p,out}$ and $\omega_{p,out}$ data generated by the MLP-31 model are compared with the actual data and are presented in Figure 4.17. Compared to the previous models, the concentration of predicted data within low error rates has decreased, and there are more data points within the $\pm 10\%$ error bands (Figure 4.17a-Figure 4.17b). It is observed that the MLP-31 model has the fewest data points within the $\pm 1\%$ error range for both $T_{p,out}$ and $\omega_{p,out}$ compared to other models (Figure 4.17b and Figure 4.17d).

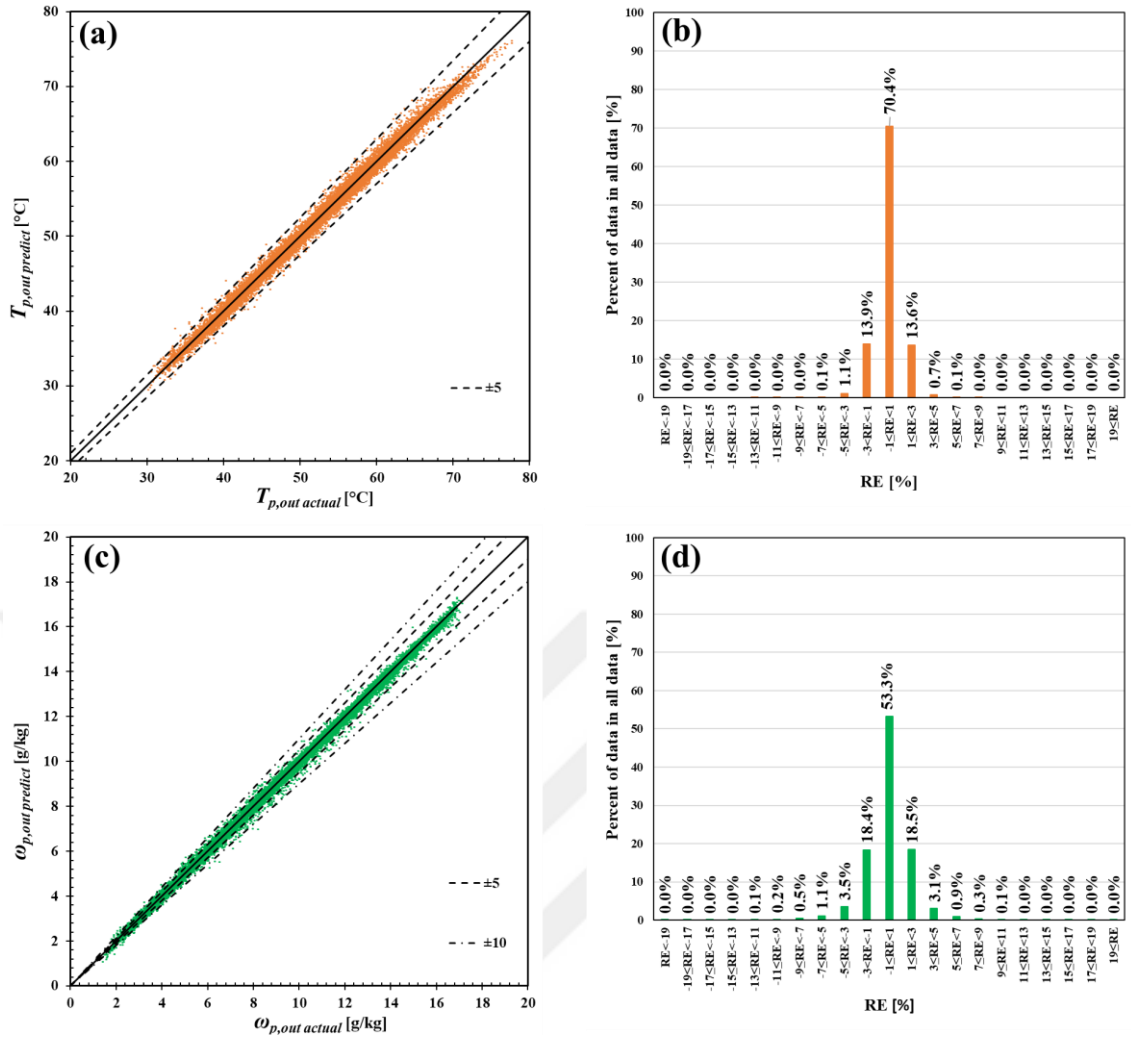


Figure 4.17. Comparison of predicted data from MLP-31 model with actual data.

Table 4.15 shows the percentage of data points within each error range produced by the developed MLP models. For $T_{p,out}$ prediction, based on the RMSE and R^2 performance parameters, the MLP-8 model is identified as the best MLP model, as seen in Table 4.14. However, when considering the maximum relative error instead of RMSE, the MLP-15 model is the best model (Table 4.15). The maximum error for the MLP-8 model is 6.43%, while for the MLP-15 model, it is 6.15%. When considering $\omega_{p,out}$, the MLP-8 model stands out among the MLP models with both the lowest RMSE and the lowest maximum error.

In summary, based on the comprehensive comparisons conducted, the MLP-8 model provides the most accurate results for both $T_{p,out}$ and $\omega_{p,out}$, with low error ranges and low maximum error.

Table 4.15. Data distribution in percentage error for Multilayer perceptrons models.

Model	Temperature					Humidity ratio				
	±5	±10	±15	±20	Max. Error	±5	±10	±15	±20	Max. Error
MLP-1	99.91	100.00	100.00	100.00	9.71	97.26	99.81	99.99	99.99	21.92
MLP-2	99.97	100.00	100.00	100.00	7.81	98.46	99.88	99.99	100.00	19.11
MLP-3	99.98	100.00	100.00	100.00	6.08	98.97	99.91	100.00	100.00	14.88
MLP-4	99.98	100.00	100.00	100.00	6.76	99.06	99.92	100.00	100.00	16.78
MLP-5	99.98	100.00	100.00	100.00	6.20	98.89	99.90	100.00	100.00	15.38
MLP-6	99.98	100.00	100.00	100.00	7.14	99.24	99.93	100.00	100.00	13.83
MLP-7	99.99	100.00	100.00	100.00	7.51	99.42	99.95	100.00	100.00	12.49
MLP-8	99.99	100.00	100.00	100.00	6.43	99.57	99.98	100.00	100.00	11.42
MLP-9	99.89	100.00	100.00	100.00	8.89	96.28	99.59	99.94	99.99	28.69
MLP-10	78.32	95.76	99.02	99.77	29.54	97.82	99.83	100.00	100.00	14.71
MLP-11	78.29	95.68	99.12	99.85	30.87	97.98	99.79	99.98	100.00	21.22
MLP-12	76.71	95.74	99.00	99.77	38.60	98.30	99.87	99.99	100.00	18.52
MLP-13	99.98	100.00	100.00	100.00	8.04	98.32	99.85	99.99	100.00	16.77
MLP-14	70.68	92.40	97.60	99.20	39.39	98.91	99.90	99.99	100.00	15.59
MLP-15	99.98	100.00	100.00	100.00	6.15	99.12	99.94	100.00	100.00	14.26
MLP-16	75.96	95.67	99.18	99.82	35.40	98.98	99.94	100.00	100.00	13.82
MLP-17	99.66	99.95	99.99	100.00	17.01	94.52	99.00	99.79	99.95	37.06
MLP-18	99.71	99.98	100.00	100.00	12.81	93.31	99.23	99.83	99.95	32.74
MLP-19	99.87	100.00	100.00	100.00	10.94	94.12	99.22	99.89	99.98	24.17
MLP-20	99.81	100.00	100.00	100.00	8.40	95.50	99.55	99.95	99.97	32.94
MLP-21	98.52	99.98	100.00	100.00	13.32	97.07	99.78	99.98	100.00	17.44
MLP-22	99.53	99.99	100.00	100.00	11.54	98.02	99.89	100.00	100.00	20.29
MLP-23	99.53	100.00	100.00	100.00	10.73	97.21	99.89	100.00	100.00	14.69
MLP-24	99.97	100.00	100.00	100.00	8.38	98.24	99.88	99.99	100.00	21.01
MLP-25	95.52	99.66	99.96	99.99	21.89	72.56	93.63	97.69	98.82	98.00
MLP-26	95.45	99.75	99.99	100.00	15.89	85.35	97.76	99.41	99.75	48.31
MLP-27	98.09	100.00	100.00	100.00	10.33	90.73	98.57	99.56	99.81	56.04
MLP-28	98.42	99.96	100.00	100.00	12.86	93.45	99.21	99.78	99.91	49.59
MLP-29	99.81	100.00	100.00	100.00	7.75	92.07	98.73	99.74	99.95	45.72
MLP-30	95.17	99.80	99.99	100.00	16.03	68.10	90.46	96.12	98.07	67.88
MLP-31	99.76	100.00	100.00	100.00	12.30	96.73	99.71	99.95	99.98	25.28
MLP-32	98.22	99.96	100.00	100.00	13.90	94.28	99.18	99.89	99.97	25.31

4.5. Comparison of All models developed

In this study, a total of 96 regression models were developed, comprising 7 Multiple Linear Regression (MLR), 45 Decision Tree (DT), 12 Support Vector Machine (SVM), and 32 Multilayer Perceptron (MLP) models. Initially, the developed models were compared among themselves, and their performance was evaluated. Following the final evaluation conducted in each section, the best model for each method (MLR, DT, SVM, MLP) was selected. In this section, the best models obtained from each method are compared (Tables 4.16 and 4.17).

Table 4.16. Comparison of the best models developed using MLR, DT, SVM, MLP for $T_{p,out}$.

Model	R ²	RMSE [°C]	Max. Error (%)	±5	±10	±15	±20
3 rd Degree Cross	0.9934	0.6018	12.21	99.627	99.988	100.000	100.000
DT-28	0.9977	0.7106	9.55	99.836	100.000	100.000	100.000
SVM-5	0.9974	0.3780	7.67	99.921	100.000	100.000	100.000
MLP-8	0.9994	0.2059	6.43	99.988	100.000	100.000	100.000

Table 4.17. Comparison of the best models developed using MLR, DT, SVM, MLP for $\omega_{p,out}$.

Model	R ²	RMSE [g/kg]	Max. Error (%)	±5	±10	±15	±20
3 rd Degree Cross	0.9972	0.1774	31.42	93.30	99.14	99.86	99.96
DT-28	0.9992	0.1903	26.76	98.53	99.75	99.92	99.98
SVM-5	0.9989	0.1082	16.42	98.67	99.90	99.99	100.00
MLP-8	0.9997	0.0693	11.42	99.57	99.98	100.00	100.00

Tables 4.16 and 4.17 present the R², RMSE, maximum error, and the percentage of data predicted within specific error ranges for $T_{p,out}$ and $\omega_{p,out}$. Considering these performance parameters, the MLP-8 model demonstrates the highest accuracy and the lowest error range for both $T_{p,out}$ and $\omega_{p,out}$.

4.6. Comparison of best model developed with the data available in the literature

The developed models were compared in the previous sections, and the best model was selected based on the determined performance parameters. In this section, the accuracy of the best model was validated using an external dataset (Alahmer et al., 2019) that was not included in the training dataset. The MLP-8 model's predictions on the validation data remain within the ±10% error band limits (Figure 4.18).

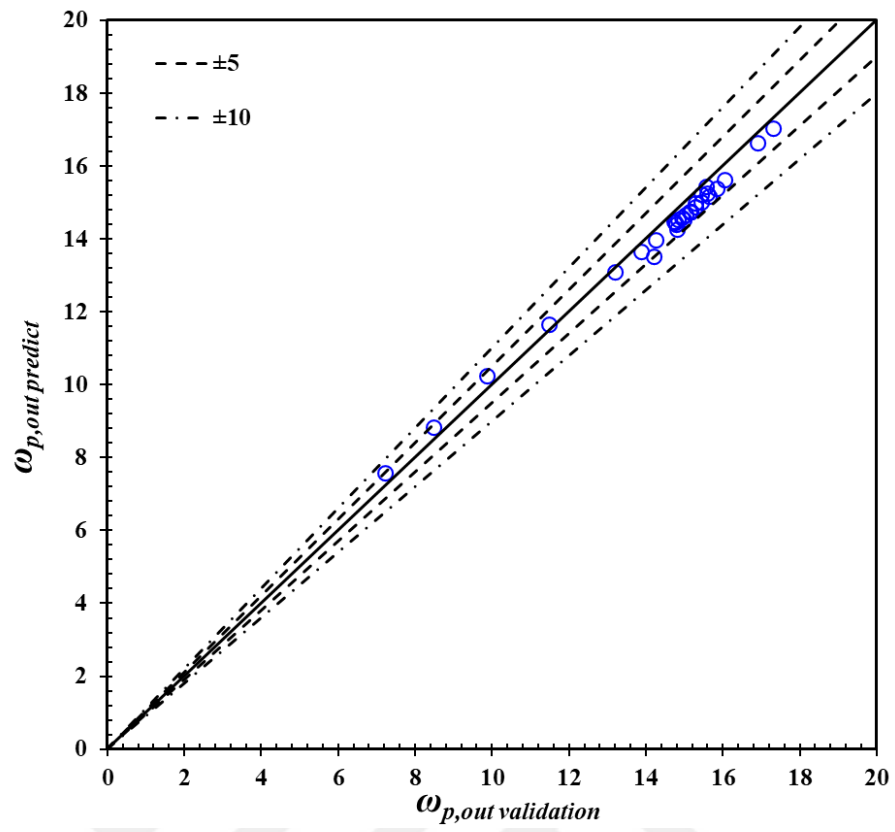


Figure 4.18. Validation of MLP-8 model for $\omega_{p,out}$.



5. CONCLUSIONS

In this study, models were developed to predict the process air outlet temperature and humidity ratio of the LT3 material based desiccant wheel with high accuracy depending upon input parameters. A total of 96 models were developed using Multiple Linear Regression, Decision Tree, Support Vector Machine, and Multilayer Perceptron methods for 32,975 different conditions. The developed models were compared based on statistical parameters such as the number of coefficients, RMSE, R^2 , and maximum relative error. Detailed results obtained from the study are listed below:

- Multiple Linear Regression (MLR): The prediction performance of MLR models increased with the degree of the equation and the addition of cross-terms. MLR models are practical for reproduction as they do not require any software.
- Among the MLR models, the Response Surface model is recommended for its less coefficients (36) and high prediction accuracy. Although the 3rd Degree Cross model is not practical due to its high number of coefficients (121), it provides more accurate predictions and is shared for usage by researchers.
- The RMSE and R^2 values of the Response Surface model were 1.0632 °C and 0.9800, respectively, while for the 3rd Degree Cross model, they were 0.6018 °C and 0.9934 for process air outlet temperature. On the other hand, for process outlet humidity ratio, the RMSE and R^2 values of the Response Surface model were 0.2998 g/kg and 0.9919, respectively, while for the 3rd Degree Cross model, they were 0.1774 g/kg and 0.9972.
- Decision Tree (DT): The Decision Tree method was examined under three main headings; Random Forest, Adaptive Boosting, and Random Tree. Among these, the Adaptive Boosting model provided more accurate predictions with lower RMSE and higher R^2 values compared to the other models.
- Among the DT models, the DT-28 coded model showed the best performance with RMSE of 0.7106 °C and R^2 of 0.9977 for process air outlet temperature, and an RMSE of 0.1903 g/kg and R^2 of 0.9991 for process air outlet humidity ratio.
- Support Vector Machine (SVM): The models developed with the SVM method were classified according to the type of kernel function. The best results were obtained from models with "Gaussian" and "rbf" kernel functions.
- The SVM-5 coded model developed with the SVM method provided the best results, with RMSE values of 0.37802 °C and 0.10817 g/kg for process outlet temperature and humidity ratio, respectively.

- Multilayer Perceptron (MLP): The effect of changes in the number of hidden layers and neurons on model performance was examined for each training function for MLP models. It was observed that the models developed with the "trainlm" function improved in performance with an increase in the number of hidden layers or neurons.
- Among the MLP models, the MLP-8 coded model provided the best results. The RMSE and R^2 values for process outlet temperature were 0.20591 °C and 0.99942, respectively, and for process outlet humidity ratio, these values were 0.06928 g/kg and 0.99970. The MLP-8 model, and its functions are presented in the appendix section for researchers.
- Overall Best Model: Among all the developed MLR, DT, SVM and MLP models, the MLP-8 provided the best predictions for the temperature and humidity ratio of the process air outlet. The RMSE values for the MLP-8 were 0.2059 °C and 0.0693 g/kg for process air outlet temperature and humidity ratio, respectively, with R^2 values of 0.9994 and 0.9997. Additionally, the maximum relative error for the process outlet temperature was 6.43%, and for the process outlet humidity ratio, it was 11.42%.

Future Works

- ❖ Multi-objective optimization can be performed for independent variables with proposed models.
- ❖ The models developed for LT3 material based desiccant wheel can be integrated into a desiccant air-conditioning system for simulation studies.
- ❖ Desiccant wheel material selection suitable for different climates can be made by using the proposed models and the silica gel models used in the literature.
- ❖ The performance of systems where silica gel and LT3 based desiccant wheels are used together can be analyzed.

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Alperen Burak Gürük graduated from Kozan Anatolian Teacher High School in 2015. He then began his bachelor's degree in the Department of Mechanical Engineering at Çukurova University in 2015. After completing his undergraduate education, he started his master's studies in the Department of Mechanical Engineering at Çukurova University. Since 2023, he has been working as a research assistant in the Department of Mechanical Engineering at Çukurova University.







APPENDICES



The best models developed are presented as supplementary file.

MATLAB files of the developed models are shared as an external file.

