ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

MODELING OF THE MARINE DIESEL ENGINES WITH COMPARATIVE MACHINE LEARNING METHODOLOGIES

Ph.D. THESIS

Mehmet İlter ÖZMEN

Department of Naval Architecture and Marine Engineering

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ISTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

GEMİ DİZEL MOTORLARIN KARŞILAŞTIRMALI MAKİNE ÖĞRENMESİ YÖNTEMLERİ İLE MODELLENMESİ

DOKTORA TEZİ

Mehmet İlter ÖZMEN
(508152012)

Gemi İnşaatı ve Gemi Makineleri Mühendisliği Anabilim Dalı

Gemi İnşaatı ve Gemi Makineleri Mühendisliği Programı

Tez Danışmanı: Prof. Dr. Osman Azmi ÖZSOYSAL

MART 2024

Mehmet İlter ÖZMEN, a Ph.D. student of İTU Graduate School student ID 508152012 successfully defended the thesis/dissertation entitled "MODELING OF THE MARINE DIESEL ENGINES WITH COMPARATIVE MACHINE LEARNING METHODOLOGIES", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Prof. Dr. Osman Azmi ÖZSOYSAL** İstanbul Technical University	....
Jury Members :	**Prof. Dr. Cemal BAYKARA** Istanbul Technical University	....
	Assoc. Prof. Dr. Yener TAŞKIN Istanbul University - Cerrahpaşa	....
	Prof. Dr. Oğuz Salim SÖĞÜT Istanbul Technical University	....
	Prof. Dr. Güven GONCA Yıldız Technical University	....

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To my family,

FOREWORD

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March 2024

Mehmet İlter ÖZMEN
(Mechanical Engineer)

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ABBREVIATIONS

ABDC	: After Bottom Dead Center
ANN	: Artificial Neural Network
ANN-E	: Artificial Neural Network Engine
AR	: Autoregressive
ARIMA	: Autoregressive Integrated Moving Average
ARIMAX	: AutoRegressive Integrated Moving Average With Exogenous Inputs
ATDC	: After Top Dead Center
ATDC	: After Top Dead Center
BC	: Bottom Center
BDC	: Bottom Dead Center
BIC	: Bayesian Information Criterion
BMEP	: Brake Mean Effective Pressure
BNN	: Bayesian Neural Network
BP	: Backpropagation
BPA	: Backpropagation Algorithm
BPNN	: Backpropagation Neural Network
BSFC	: Brake Specific Fuel Consumption
BSFM	: Brake Specific Fuel Consumption
BTDC	: Before Top Dead Center
BTE	: Brake Thermal Efficiency
BTM	: Brake Thermal Efficiency
CN	: Cetane Number
CNG	: Compressed Natural Gas
CNN	: Convolutional Neural Networks
CO	: Carbon Monoxides
CO2	: Carbon Dioxide
COV	: Coefficient of Variation
CRDI	: Common Rail Direct Injection
CRS	: Common-Rail Systems
DEE	: Diethyl Ether

DGS : Diesel Generator Set
DI : Direct Injection
DKL : Deep Kernel Learning
DNN : Deep Neural Network
DOC : Diesel Oxidation Catalyst
DoE : Design of Experiments
DPF : Diesel Particulate Filters
DWI : Direct Water Injection
EBP : Exhaust Back Pressure
ECM : Engine Control Module
ECU : Electronic Engine Control Unit
EDC : Engine Diesel Control
EGR : Exhaust Gas Recirculation
EGT : Exhaust Gas Temperature
EIAPP : Engine International Air Pollution Prevention
ELM : Extreme Learning Machines
EMS : Engine Management System
ERT : Ensemble of Regression Tree
EVO : Exhaust Valve Opening
FADEC : Full Authority Digital Engine Control
FBNNs : Feedforward Neural Networks
FNN : Feedback Neural Networks
GA : Genetic Algorithms
GoF : Goodness of Fitting
GP : Gaussian Process
GPR : Gaussian Process Regression
GRU : Gated Recurrent Unit
HAM : Humid Air Motor
HC : Hydrocarbons
HCCI : Homogeneous Charge Compression Ignition
HDMR : High-Dimensional Model Representation
HIL : Hardware In the Lopp
IC : Inlet Closure
ICE : Internal Combustion Engines
IMEP : Indicated Mean Effective Pressure

IMO : International Maritime Organization
LHV : Lower heating Value
LM : Levenberg-Marquardt
LR : Linear Regression
LS-SVM : Least Squares Support Vector Machine
MA : Moving Average
MAE : Mean Absolute Error
MAPE : Mean Absolute Percentage Errors
MARPOL : International Convention for the Prevention of Pollution from Ships
ML : Machine Learning
MLP : Multi-layer Perceptron
MLR : Multiple Linear Regression
MRE : Mean Relative Error
MSE : Mean Square Error
MSLE : Mean Square Logaritnic Error
MVEM : Mean Value Engine Model
NARX : Nonlinear AutoRegressive with eXogenous Inputs
NLARX : Non-Linear Autoregressive Models with Exogenous Inputs
NOx : Nitrogen Oxide Emission
NRMSE : Normalized Root Mean Square Error
NTRC : Non-Road-Transient-Cycle
OBD : On-Board Diagnostic
PM : Particulate Matter
RAE : Relative Absolute Error
RBFNN : Radial Basis Function Neural Network
RegARMA : Regression with AutoRegressive Moving Average
RF : Random Forests
RMS : Root Mean Square
RMSE : Root Mean Square Error
RNN : Recurrent Neural Networks
RPM : Revolutions Per Minute
RSM : Response Surface Methodology
RT : Regression Tree
RTPC : Real-Time Processing Computer
RVM : Relevance Vector Machine

SCG : Scaled Conjugate Gradient

SCR : Selective Catalytic Reduction

SECAs : Sulphur Emissions Control Areas

SI : Spark Ignition

SISO : Single-Input Single-Output

SLP : Single-layer Perceptron

SOI : Start Of Fuel Injection

SOx : Sulphur Oxides

SVM : Support Vector Machines

TC : Top Center

TDC : Top Dead Center

UBHC : Unburned Hydrocarbon

UIS : Unit Injector System

VGT : Variable Geometry Turbocharhing

VVT : Variable Valve Trains

WCO : Waste Cooking Oil

SYMBOLS

$\mathbf{y_u(k)}$	: Output vector of polynomial regression
$\mathbf{k}$	: Design matrix of polynomial regression
$\mathbf{K}$	: Parameter vector for polynomial regression
$\mathbf{P}$	: Engine power
$\boldsymbol{\pi}$	: Pi number
$\mathbf{n}$	: Engine speed
$\mathbf{M}$	: Engine torque
$\boldsymbol{\lambda}$	: Lambda (Air–fuel equivalence ratio)
g/kWh	: Gram per kilowatt hour
$\mathbf{h(x)}$	: Output variable of linear regression
$\mathbf{w}$	: Coefficient of linear regression
$\mathbf{b}$	: Bias (basic error) of linear regression
$\mathbf{x}$	: Input variable of linear regression
$\mathbf{j}$	: Cost function
$\mathbf{m}$	: Number of data points to calculate cost function via mean squared error
$\mathbf{y_t}$	: Engine model output at time t, for the Multiple Linear Regression (MLR) model
$\mathbf{c}$	: Intercept value for MLR
$\boldsymbol{\emptyset_i}$	: Coefficient vector of MLR
$\mathbf{X_i}$	: Predictor time series for MLR
$\boldsymbol{\varepsilon_t}$	: Error term accounting for unobserved factors for MLR
$\mathbf{L}$	: Number of layers for Multi Layer Perceptron (MLP)
$\mathbf{W_i}$	: Weight matrix for layer i, for MLP
$\mathbf{f}$	: Activation function for MLP
$\boldsymbol{\Delta w}$	: Weight update for a weight w, for Back Propagation (BP)
$\boldsymbol{\eta}$	: Learning rate of the BP
$\boldsymbol{\partial J, \partial w}$	: Partial differentials of cost function j, and weight w
$\mathbf{y_k}$	: k-th neuron in the hidden layer of Radial Basis Function (RBF)
$\mathbf{c_k}$	: Center of the k-th neuron of RBF

$\boldsymbol{\sigma_k}$	: Width parameter of RBF
$\emptyset$	: Radial Basis Function (RBF)
$\mathbf{H}$	: Hidden layer output of Extreme Learning Machine (ELM)
$\boldsymbol{\sigma}$	: Activation function of ELM
$\mathbf{W_{in}}$	: Input-to-hidden layer weight matrix of ELM
$\mathbf{B_{in}}$	: Bias for the hidden layer of ELM
$\mathbf{W_{out}}$	: Output layer weights of ELM
$\mathbf{h_t}$	: Output variable of Recurrent Neural Network (RNN) at time t
$\mathbf{f_{RNN}}$	: Activation function of RNN
$\mathbf{W_{hx}}$, $\mathbf{W_{hh}}$	: Weight matrices of RNN
$\mathbf{b_h}$	: Bias vector of RNN
$\mathbf{y(t)}$	: Estimated output at time t, of NARX
$\mathbf{u(t)}$	: Exogenous inputs at time t, of NARX
$\mathbf{f_{NARX}}$	: Nonlinear function of NARX
$\mathbf{p}$	: Autoregressive order of ARIMAX and RegARMA
$\mathbf{D}$	: Degree of integration of ARIMAX and RegARMA
$\mathbf{r}$	: Number of predictors of ARIMAX and RegARMA
$\mathbf{q}$	: Moving average order of ARIMAX and RegARMA
$\mathbf{c_{ARMA}}$	: Constant of ARIMAX and RegARMA
$\boldsymbol{\varepsilon_t}$	: Constant error of ARIMAX and RegARMA
$\emptyset(\mathbf{L}), \boldsymbol{\theta}(\mathbf{L})$	: Lag operators of ARIMAX and RegARMA
$\mathbf{X_r}$	: Input variable vector of ARIMAX and RegARMA
$\boldsymbol{\beta_r}$	: Coefficient matrix of ARIMAX and RegARMA
$\boldsymbol{\mu_t}$	: Constant error of RegARMA
$\mathbf{N}$	: Number of sample points to calculate average for MAE and MSE
$\sqrt{\mathbf{MSE}}$	: Root of mean squared error (MSE)
$\mathbf{n_{BIC}}$	: Number of data points for BIC
$\mathbf{p_{BIC}}$	: Degree of freedom represents complexity of BIC metric
$\mathbf{log}$	: Logarithm
$\hat{y}_i$	: i-th index of estimated output of BIC
$\mathbf{R}^2$	: Coefficient of determination

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MODELING OF THE MARINE DIESEL ENGINES WITH COMPARATIVE MACHINE LEARNING METHODOLOGIES

SUMMARY

The marine industry is undergoing a transformative phase, marked by escalating environmental expectations, technological advancements, and the growing influence of electric vehicles alongside traditional diesel engines. Despite these shifts, legislative frameworks and performance standards are continually evolving, making it imperative to scrutinize critical variables. In the complex task of developing and calibrating modern combustion engines, especially given stringent emission standards and the necessity to comply with real driving emissions regulations, the understanding of internal engine processes becomes paramount.

In the pursuit of enhanced performance and reduced emissions, the precise control of engine variables stands out as a major factor. Designing effective control algorithms requires an accurate model that reflects the intricacies of engine dynamics. The conventional approach of real-time testing proves both time-consuming and expensive, emphasizing the urgency for alternative methodologies. Acknowledging these challenges, the industry is increasingly turning to virtual testing environments, simulations, and modeling as integral components of the design and calibration process.

Given the time-consuming and expensive nature of real-time testing and vehicle processes, the role of modeling and simulation has become pivotal. Modeling serves as a cornerstone in addressing the challenges posed by the quest for enhanced efficiency and reduced emissions in internal combustion engines. Traditional methods and cutting-edge technologies have been explored to comprehend and optimize engine performance. Traditional physical model-based approaches offer insights into challenging-to-measure phenomena, proving robust as input data changes. However, as modeling depth increases, computational power demands soar. In response, data-driven machine learning methods stand out as an alternative, capable of achieving high accuracy, albeit relying heavily on the quality of training data.

Highlighting the pivotal role of modeling, data-driven approaches emerge as a linchpin in this journey. The flexibility of data-driven modeling methods, especially suited for the intricate dynamics of non-linear engines, brings advantages in terms of accuracy and efficiency. As the industry endeavors to find the optimum method concerning data volume, quality, variety, and complexity, this study undertakes the task of exploring and comparing a spectrum of commonly used data centric methods found in the literature.

This study encapsulates a comprehensive exploration of widely utilized data driven methods found in the literature, including ANN, SVM, and ELM. Going beyond the conventional, the research introduces novel approaches such as NARX, ARIMAX, and RegARMA, all of which have demonstrated significant success in estimation tasks. By

amalgamating established methodologies with innovative techniques, this research aims to contribute not only to academic discourse but also to the practical toolkit available for modeling marine engine behavior. The goal is to empower the industry with versatile, accurate, and efficient modeling strategies that align seamlessly with the dynamic landscape of marine propulsion systems. As environmental expectations soar and technological possibilities expand, the role of modeling in steering the marine industry toward sustainable and high-performance solutions has never been more pivotal.

In addition, practical experiences such as collecting data from two separate diesel engines and a different engine type, the Wankel engine, processing the collected data, and using software using relevant machine learning methods are also reflected in this study. This study reviews machine learning and related time series methods, which are frequently used in the literature to model diesel engines, and conducts a comparative study on these methods, in this sense, in order to design control algorithms that can overcome the performance and emission restrictions that await especially ship diesel engines, with a high prediction rate. can be considered as a study that can contribute to the literature on creating a realistic engine model.

GEMİ DİZEL MOTORLARIN KARŞILAŞTIRMALI MAKİNE ÖĞRENMESİ YÖNTEMLERİ İLE MODELLENMESİ

ÖZET

Artan çevresel beklentiler ve teknolojik gelişmeler ve elektrikli araçların endüstride kullanımının yaygınlaşmasının etkisiyle geleneksel dizel motorlar halen liderlik ettikleri denizcilik ve ağır yük endüstrilerinde de performans ve emisyon standartları çerçevesinde iyileştirmelere ihtiyaç duymaktadır. Sürekli gelişen performans beklentileri ve güncellenen emisyon standartlarına uyma zorunluluğu içten yanmalı motorların geliştirilmesi anlamında motor mekaniğinin ve performans ve emisyona etki eden faktörlerin düzgün tespitini gerektirmektedir. Günümüz teknolojisinde motor dinamiğinin performans ve emisyon kriterleri ile etkileşimi, yakıtın ve havanın karıştırıldıkları miktar, zaman ve bunlara etki edebilen çeşitli parametreler elektronik sistemler ile kontrol edilmekte ve bu kriterlerin sağlanmasında kontrolcü tasarımı da önemli rol oynamaktadır.

Denizcilik endüstrisi için Uluslararası Denizcilik Örgütü'nün belirlediği emisyon kısıtları, azot oksit (NOx) ve sülfür oksit (SOx) özelinde yıllar geçtikçe artmaktadır. Bu kapsamda belirli periyotlarda güncellenen ve son versiyonu 2016 yılında açıklanan Denizlerin Gemilerden Kirlenmesini Önleme Uluslararası Sözleşmesi'nin ilgili ekinde, bir önceki yıl olan 2011'deki kısıtlamalara nazaran motor devir sayısına göre değişmekle beraber ortalama 4 kat kısıtlamaya gidilmiştir. Yeni üretilecek gemilerin direkt olarak tabi olduğu bu güncelleme var olan gemilere de azaltılmış NOx emisyonları için teşvikler sunmaktadır. Egzoz gazının silindir içine alınmasıyla yanma sıcaklığını ve oksidasyonu azaltan 'Egzoz gazı resirkülasyonu' ve egzoz gazına özel bir çözelti püskürtülmesiyle azot oksidi azot ve su buharına indirgeyen 'Seçici katalitik indirgeme' gibi NOx azaltma mekanizmalarının veya alternatif yakıtların (sıvılaştırılmış doğalgaz gibi) kullanılması veya ilgili araştırma geliştirme çalışmaları bu teşvikler kapsamındadır. NOx azaltıcı mekanizmalar NOx emisyonlarının azaltılmasına direkt etki eden ve bu kapsamda emisyon kısıtlarını sağlayabilmek için tercih edilen mekanizmalar olmakla birlikte, araştırma geliştirme, entegrasyon ve bakım faliyetleri düşünüldüğünde güncel operasyonun optimize kontrol algoritmaları ile iyileştirimesi bu anlamda kullanışlı bir alternatif olarak düşünülebilir. Emisyon kısıtlamalarını karşılamak için geliştirilen kontrolcülerin bir diğer avantajı, gemi işletmecilerinin ceza ödemekten kaçınmalarına yardımcı olması olarak düşünülmektedir. Emisyonlarla ilgili düzenlemelere uyum sağlamak, cezai yaptırımların yanı sıra itibar kaybı riski de taşıyacağından, emisyon iyileştirmeleri bu kapsamda da önem arz eden bir unsurdur. Performans kriteri olarak dizel motorun aynı gücü daha az yakıtla sağlaması veya yakıt tüketiminin azaltılması ön plana çıkmaktadır. Bu kriteri sağlamak için de elektronik kontrol sistemlerinin ve algortimalarının iyileştirilmesi önem arz eder. Daha iyi motor kontrolü, yakıt tüketiminin azaltılmasını, dolayısıyla işletme maliyetlerinin düşürülmesini sağlar. Ayrıca motor bileşenlerinin ömrünün uzamasının bakım maliyetlerinin de azalmasına katkı sağlayacağı düşünülmektedir. Dolayısıyla emisyonların azaltılması çevresel

etkilerin minimize edilmesine, yakıt tüketiminin azaltılması da fosil yakıt kullanımının ve karbon ayak izinin düşmesine katkıda bulunrak gemi endüstrisinde sürdürülebilirlik çabalarının temelini oluşturur. Bu kapsamda geliştirilme ve optimize edilme faliyetleri devam eden kontrolcüler, bu prosesin önemli bir parçası konumundadır.

Dizel motorun kontrolü temel olarak motorun hızı ve torkunun emisyon kısıtlamaları altında motoru optimum kondisyonda çalıştıracak şekilde ayarlanması şeklinde açıklanabilir. Bu operasyonda temel eyleyici olarak enjektörler, ray basınç valfi, egzoz gaz resirkülasyonu valfi, turboşarj valfi, sensör olarak atmosfer basınç ve sıcaklığı, hava debimetresi, giriş manifoldu hava basınç ve sıcaklığı, ray basıncı, soğutma suyu sıcaklığı, egzoz mekanizması basınç, sıcaklık ve emisyon sensörleri sıralanabilir. Enjektöler özelinde hem enerjilendirilme süreleri hem de enerjilendirilme başlangıç periyotları düşünüldüğünde saniyenin yüzde birine tekabül edecek yüksek hızlı ve çözünürlüklü işlem kabiliyeti gerekmektedir. Bu anlamda kontrolcülerin mikroişlemci yeteneklerinin yanında gerçek zamanlı test sisteminde sensör ve eyleyici konfigürasyonunun yönetilmesi, motorun nihai ürüne dönüşmeden önce tamamlanması gereken ve yatırım maliyeti, işlem kompleksliği ve zaman anlamında efor gerektiren önemli bir prosestir.

Etkili kontrol algoritmalarının tasarlanması ve bu algoritmaların optimize edilmesi, gerçek bir motor veya test düzeneğinin sürekli kullanımının zaman alıcı ve maliyetli olduğu da göz önünde bulundurulduğunda, motorun fiziksel ve matematiksel olarak gerçeğe yakın bir şekilde bilgisayar ortamında modellenmesi gerekliliğini doğurmaktadır. Bu gereklilğin kabul eden endüstri, tasarım ve kalibrasyon sürecinin ayrılmaz bileşenleri olarak sanal test ortamlarına, simülasyonlara ve modellemeye giderek daha fazla yönelmektedir.

Modelleme, motorun çeşitli prosesleri için momentum, ısı, kütle denklemleri, kimyasal reaksiyon denklemleri, fiziksel denklemler ve matematiksel hesaplamalar kullanılarak yapılabilir. Bununla birlikte tüm bu idealize edilmiş denklemler çok sayıda varsayıma ve basitleştirmeye ihtiyaç duyarlar. Bu tarz hesaplama yoğunluklu denklemler güvenilir bir simülasyon için önceden tanımlanması veya tahmin edilmesi gereken motora özgü birçok parametre gerektirir. Dolayısıyla bu denklemler bir noktada motorun doğrusal olmayan dinamiklerini yüksek oranda yansıtma konusunda eksik kalabilirler. Fiziksel kanunlara dayanan geleneksel modelleme yöntemlerine alternatif olarak, motorun gerçek test verilerinin belli oranda kullanıldığı haritalama metodları tercih edilmektedir. Bu metodlar motorun kritik parametrelerinin, önceden belirlenen rejimlerde toplanan gerçek datalar kullanılarak yansıtıldığı ve fiziksel kanunlara nazaran işlem karmaşıklığı ve lineer olmayan davranışları daha az olan metodlardır. Haritalama metodu da motorun tüm rejimleri için her veri noktasını kullanmanın işlem karmaşıklığını artıracağı düşünüldüğünde sınırlı operasyon koşullarında kullanışlı olarak kabul edilmektedir. Bu nedenle dizel motor gibi doğrusal olmayan dinamik bir davranışa sahip sistemleri modellemek için son dönemlerde verimli, hızlı, kestirim kabiliyeti yüksek olan veriye dayalı makine öğrenmesi metodları kullanılmaktadır. Makine öğrenmesi, bilgisayar sistemlerinin veriye dayalı deneyimlerden prosesi öğrenmesini sağlayan bir yöntemdir. Makine öğrenmesinin en yaygın temsilcisi olarak yapay sinir ağları, insan beyninin çalışma şeklini örnek alan, dışarıdan aldığı bilgiyi toplayıp değerlendiren, katmanlar halindeki nöronlardan geçiren ve yorumlayan, hatayı tespit edip optimum seviyede düzeltme yeteneğine sahip olan matematiksel öğrenme metodlarıdır. Geniş bir uygulama yelpazesinde kullanılmakta olan makine öğrenmesi yöntemleri, görüntü tanıma, doğal dil işleme, lineer olmayan sistem davranışlarının (örneğin motor) modellenmesi, tahmin ve karar verme gibi alanlarda verimli bir şekilde kullanılmaktadır.

Gerçek motor üzerinden toplanan verilerin birbirleri arasında matematiksel veya istatistiksel bağ kurulması ile oluşturulan makine öğrenmesi yöntemleri esneklik ve gerçek verilere yakınlık anlamında geleneksel yöntemlere avantaj sağlamaktadır. Uygulanacak olan makine öğrenmesi yöntemi, veri sayısı niteliği, çeşitliliği karmaşıklığı ve modellenmesi istenen sisteme uyumluluğu gibi kriterlere ve kurulmak istenen mimariye göre farklılık gösterebilir. Bu anlamda modellenmek istenen sistem davranışını yansıtabilecek makine öğrenmesi yöntemine karar vermek, işlem karmaşıklığının, işlem süresinin ve hatalı tahminin önüne geçmek açısından önem taşımaktadır. Bu çalışma da literatürde bu anlamda değişiklik gösteren modelleme yöntemlerini inceleme ve birbirleriyle karşılaştırma amacını taşımaktadır.

Genel bir değerlendirme olarak da değerlendirilebilecek olan bu çalışma, yapay sinir ağları, öğrenme makineleri ve destek vektör makineleri olmak üzere literatürde yaygın olarak kullanılan veri odaklı yöntemlerin kapsamlı bir incelemesini içermektedir. Bu içerikte yöntemlerin matematiksel ifadeleri, görsel karşılıkları ve kullanım avantajları detaylandırılmaktadır. Geleneksel yöntemlere ilaven, Exogenous girişli Doğrusal Olmayan Otomatik Gerileme (NARX), Exogenous girdili Otomatik Gerilemeli Entegre Hareketli Ortalama (ARIMAX) ve Otomatik Gerilemeli Hareketli Ortalamalı Regresyon (RegARMA) gibi dizel motor modellenmesinde özgün yaklaşımlar ve bu yaklaşımların birbirleri ile karşılaştırıldığı uluslararası bir akademik yayın yapılmıştır. İstatistik biliminde de kullanılan, veri noktalarının zamana bağlı değiştiği bu yöntemler, verilerin geçmişte aldığı değerlerin değişimini gelecekte alacağı değerleri kestirmek için kullanabilmekte ve karmaşık verilerin yüksek doğrulukta tahmin edilmesinde avantajlı olarak değerlendirilmektedir.

Bununla birlikte bu çalışmada dizel motor ve farkli bir motor tipi olarak Wankel motorundan veri toplama, toplanan veriyi işleme, ilgili makine öğrenmesi metodlarının kullanıldığı yazılımları kullanma gibi pratik deneyimler de yansıtılmıştır. Temel çalışma konusu dizel motor olmakla birlikte, dizel motor için istenen veri setine erişme sürecinde dinamometre test düzeneği hazır olan ve veri çeşitliliği yeterli olan bir Wankel motoru, temel yapay sinir ağları yöntemini test edebilmek adına başarıyla kullanılmıştır. Tez kapsamında yayınlanan makalelerde, istenen performans ve emisyonu (örneğin yakıt tüketimi ve NOx) incelemek ve özgün metodlarla modellemek için sistem davranışını yansıtabilecek giriş çıkış verilerine ihtiyaç duyulmuş ve bu ihtiyaca yönelik ölçümler planlanmıştır. Dizel motordan istenen nitelikte, çeşitte ve sayıda veriyi elde edebilmek için ilgili deney düzeneğinin kurulması veya kurulu bir deney düzeneğinin ihtiyaca yönelik enstrümante edilmesi (sensör, eyleyici ve ölçüm ekipmanları açısından) gerekmektedir. İmkanlar dahilinde gemi seyir testleri de sistem davranışını yansıtabilecek veriyi toplayabilmek için uygun ortamlardır. Bu kapsamda hem dizel motor hem de Wankel motoru için enstrümante bir dinamometre test düzeneğinden veri toplanmıştır. Bu veriler belirli ön işlemlerden geçirilerek modellenmeye hazır hale getirilmiştir. Karar verilen model mimarisi ve modelin matematiksel detayları (parametreleri, aktivasyon fonksiyonu, optimizasyon algoritması, nöron ve katman sayısı gibi) ilgili simulasyon yazılımı programı vasıtasıyla kurulmuştur. Modeller test sürecini tamamladıktan sonra çıkış verilerini yüksek doğrulukta bir kestirim performansıyla yansıttığı görülmüştür. Ayrıca birbirinden farklı motor tipleri ile çalışmak ve bu farklılıktan bağımsız olarak makine öğrenmesi yöntemlerinin yüksek doğrulukta tahmin edebildiklerini tespit etmek de bu yöntemlerin farklı sistemlere adaptasyonunu gözlemlemek adına önem taşımaktadır.

Bu çalışma literatürde dizel motor modellemek için sıklıkla kullanılan makine öğrenmesi ve bunlarla ilişkin ancak nispeten sınırlı kullanımı olan zaman serisi metodlarının gözden geçirildiği, bu metodlar ile ilgili karşılaştırmalı özgün bir çalışmanın yapıldığı, bu anlamda özellikle gemi dizel motorlarını bekleyen performans ve emisyon kısıtlamalarının üstesinden gelebilecek kontrol algoritmalarının tasarlanması adına, kestirim oranı yüksek, gerçeğe yakın bir motor modeli oluşturma konusunda literatüre katkı sağlayabilecek bir çalışma olarak kabul edilebilir.

1. INTRODUCTION

Engines are machines in which the energy released as a result of the chemical reaction formed by the combustion of fuel is converted into mechanical energy. The rise in temperature within the fluid, which serves as the operational medium in the power plant, stems from the heat generated during oxidation reactions involving elements like carbon or hydrogen. Accordingly, engines can be categorized as internal combustion engine (such as Otto, Diesel, Wankel engines) when the combustion occurs with the operational fluid itself, and external combustion engines (such as heat exchanger, stream turbine plants, Stirling engines) that the fuel is burned outside the engine cylinder, in a place separated from the engine [73][78]. External combustion engines have relatively low noise and vibration and tend to be more environmentally friendly and with lower emissions due to their low combustion temperature and pressure [75]. However, since they have a lower power and take up more space than internal combustion engines, nowadays, internal combustion engines are mostly preferred for transportation-based power generation.

Internal combustion engines, of which the most familiar types are Otto engines (spark ignition) and Diesel engines (compression); They are commonly employed as a power source in many areas of industry from automotive to heavy industry due to their simplicity, high power/weight ratio and robustness [74]. Although they have a similar structure in terms of their basic working principle (intake, compression, ignition, exhaust), Otto engines obtain mechanical energy by igniting the air-fuel mixture after it is mixed and compressed in the cylinder, while in Diesel engines compression is applied solely to the air within the cylinder and high energy is obtained by spraying fuel at pressure and temperature.

In addition to the ignition type of the fuel, which is one of their main differences, they also differ from each other in terms of fuel type, fuel/air mixture ratio, fuel burning speed, and cylinder compression ratio. Otto engines, which use petroleum as fuel, are mostly used in the automotive industry due to their lighter weight, more homogenization of the fuel-air mixture, and their ability to reach high speeds [76].

Diesel fueled engines discussed in this study, on the other hand, are widely used in locomotives, ships, construction equipment and numerous similar industrial applications besides the automotive industry, considering their high compression ratio and thermal efficiency.

Physical parameters such as displacement, cam profile and compression ratio indicate a range of performance, fuel economy and emission characteristics for conventional mechanically controlled engines. However, periodically updated emission standards within the scope of environmental protection measures, the need for high efficiency with developing technology and competitive commercial concerns have required the internal combustion engines to be equipped with electronically controlled equipment, especially for fuel consumption and emission improvements, apart from mechanical measures. Considering the non-linear properties of diesel engines, the control of actuators and design of related algorithms are important in terms of determining the optimum operating range [77].

Along with high power generation, fuel consumption and emissions from combustion are among the most important performance criteria of diesel engines. Mechanical and electronic control techniques have been applied to improve diesel engine performance and reduce emissions, and they are still being developed. Parameters affecting these outputs are determined for performance analysis and controls. The aim here is to manipulate key engine variables such that the engine operates with optimum performance (maximum power, minimum fuel consumption and emissions) by controlling actuators (injectors, valves) and actuator-related parameters.

In order for the electronic control units for diesel engines to function functionally and to meet the performance criteria of the diesel engine, algorithms must be designed to control the actuators under certain conditions. These algorithms are designed as code base or model base and tested on the computer environment, on the processor and on the latest engine. In order to develop computer-based software, engine models that simulate the diesel engine with which the control software will work are also set up in the computer environment. Engine modeling can generally be done by formulating the chemical or physical specs of the engine or mapping it from experimental data, and in its popular form today which is the main discussion of this work, by establishing a mathematical relationship between the data independent of engine physics [79].

1.1 Engine Modeling Basics

Multi-domain systems such as Internal Combustion Engines (ICE’s), can be determined with system theory in terms of temporality. Therefore mathematical models can be employed to represent the static and dynamic characteristics of the system elements. These mathematical models can be categorized as theoretical (physical) and experimental modeling as mentioned above. ICE’s, parts of working cycles and peripheral equipments requires combined mathematical models for different areas such as mechanics, combustion, thermodynamic, electricity. Therefore the theoretical modeling has also unified representation ability for interdisciplinary physical domains that becomes an advantage for computer aided modeling [80].

1.1.1 Theoretical modeling

In principle, this may represented via fundamental equations and process elements from different domains as follows;

- Balance equations, derived from conservation laws, describe the global behavior for mass, energy and momentum.
- Constitutive equations with special physical laws
- Phenomenon equations, if irreversible process take place [80].

1.1.1.1 Process elements

When expressing fundamental equations, it's crucial to differentiate between processes characterized by distributed parameters and lumped parameters. In cases involving distributed parameters, consideration of time and space dependencies becomes essential, typically resulting in partial differential equations. Conversely, when the impact of spatial variability is minimal, the process can be analyzed using lumped parameters, resulting in ordinary differential equations in relation to time. Combustion engines and drivetrains often encompass both types of parameters, although lumped parameters are frequently applicable [80].

Even when explicit solutions are unattainable, individual equations provide valuable insights into the model's structure. It's worth noting that constitutive equations frequently introduce nonlinear relationships. Process elements can be classified based on controllability and the presence of an auxiliary energy source. Passive elements involve the transfer of quantities without control from an additional source, such as capacitances, fixed gear transmissions, or fans with a constant speed. On the other hand, active elements manipulate quantities through actuators, often requiring electrical or mechanical auxiliary energy [80].

1.1.1.2 Fundemental equations

The fundamental equations, conversely, pertain to processes with lumped parameters. Balance equations align with conservation principles for mass or energy, addressing confined regions where neither mass nor energy exits. They are used for sources, storages that are represented as linear equations [80].

Constitutive equations execute the consistency between the inputs and outputs of process elements by specific physical laws in analytic form. When process elements are considered as electrical terminals, the potential difference between the elements can be defined as ‘effort’. (Voltage, pressure, or force difference can be given as example) Variables such as electric current, velocity, volume can also be defined as ‘flow’ variables entering from one terminal to another. Potential differences and flow variables can be defined as generalized power variables. Shaping the constitutive equations with this structure is advantageous for modeling mechatronic (mechanic, hydraulic, electrical, electronic) systems [80].

1.1.1.3 Time and rotational angle dependent models

Internal combustion engines generally exhibit a reciprocating motion depending on the rotation angle of the crankshaft. When considering the design of engine control unit (ECU) control algorithms, simplifications can be made by considering only the dominant dynamic effects in relation to key variables of the engine such as fuel consumption, torque, manifold absolute pressure. The critical variables such as fuel injection, ignition, injection pressure, air intake, valve timing which influence the single combusiton can be determined by way of crank angle [80].

Conversely, certain processes related to engine compnents outside the cylinders can be characterized behaviour is often disregarded, particularly in multi-cylinder engines, due to the damping effect caused by gas or thermal storages, making the reciprocating behavior of the cylinder less significant. Examples of such processes include manifold pressure, air flow, turbocharger speed, as well as emissions. When fluctuations induced by the working stroke are omitted, the resultant models are referred to as mean-value models. The connection between the crankshaft angle and engine speed can be expressed under the assumption that the mean value of the crankshaft speed remains relatively constant throughout one cycle. This allows for the consideration of a consistent engine speed in certain crank-angle-dependent models.

According to this, dynamic models including internal combustion engine can be represented as continuous time (time based) models and discrete time (sample based) models. Laplace transform (time base function to frequency base function) and z-transform (discrete function to frequency base function) methods are used to represent the transfer function of related domain [80].

1.1.1.4 Semi physical models

Theoretical models define the functional connection between physical and chemical variables through parameters, while experiments involve numeric parameters. The effective modeling of internal combustion engines involves a judicious aggregation of theoretical (white-box) and experimental (black-box) models. (Figure 1.1)

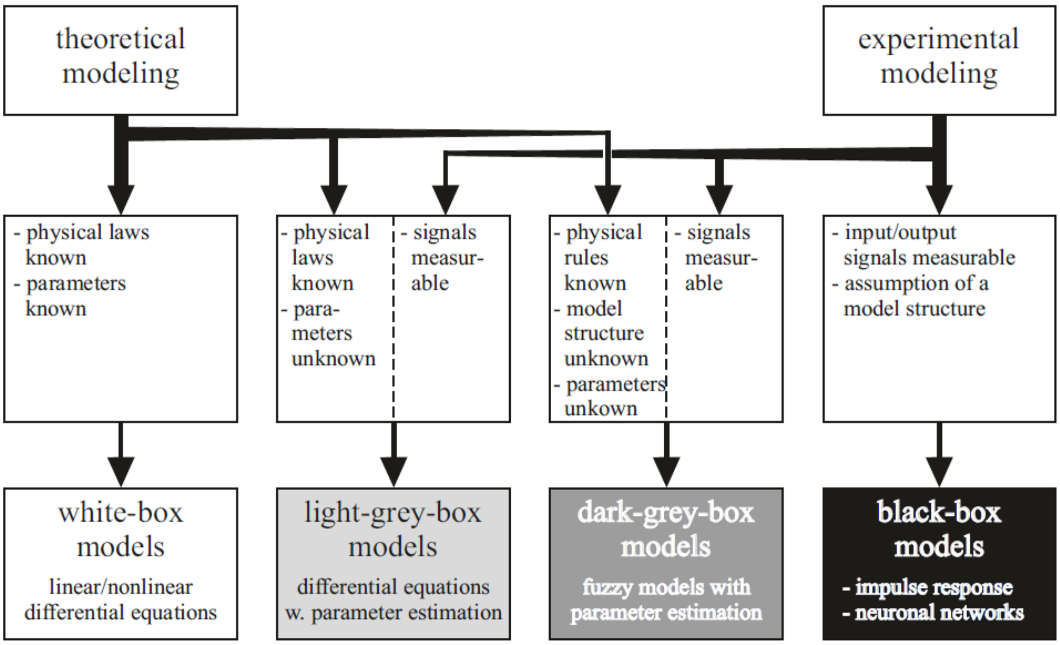

Figure 1.1 : Combinations of theoretical and experimental modeling [80].

1.1.2 Experimental modeling

Theoretical modeling fails short of modeling some engine processes since the mathematical formulation is not clearly recognised or the computational effort is extensive regarding diagnosis and control. Pressure and temperature development, spray development, combustion and emission are generic examples of complex formulation.

On the other hand, there are some parts that even if theoretical model is enable, necessary parameters are not implicitly recognised. Examples are the internal heat transfer at intake manifold, mechanical parts of the turbocharger, pumps and crankshaft. In such kind of cases, when theoretical modeling gives the general perspective, detailed precise models can only be obtained by experimental data collected from test environments. Experimental modeling can be evaluated for different behaviors of engines (such as stationary and dynamic) since the modeling way is based on identification of linear, nonlinear and time varying processes. Therefore, various identification methos as look-up tables (maps), parameter estimation and neural networks are advised to use for experimental modeling [80].

1.1.2.1 Look-up tables and maps

Commonly utilized in practical applications for one or two inputs, curves or look-up tables serve as prevalent nonlinear static models, particularly in the realm of nonlinear control. They offer a flexible depiction for nonlinearity between the variables. While advantageous for adapting individual data points to changing conditions, the exponential increase in data points with more inputs poses a drawback [80]. Parametric model alternatives, such as fuzzy models or neural networks, require fewer parameters and reduced storage but entail higher computational complexity [80].

1.1.2.2 Parameters estimation

Direct measurements from look-up tables lack the ability to suppress noisy outputs. This limitation can be overcome by adopting a polynomial approach that necessitates the collection of output measurements, denoted as y(k), for various inputs, u(k), covering the relevant range. This process results in a usable output for a given input and sample k (1.1) as shown in Figure 1.2.

$$y_u(k) = K_0(k) + u(k)K_1 + u^2(k)K_2 + \cdots + u^q(k)K_q \tag{1.1}$$

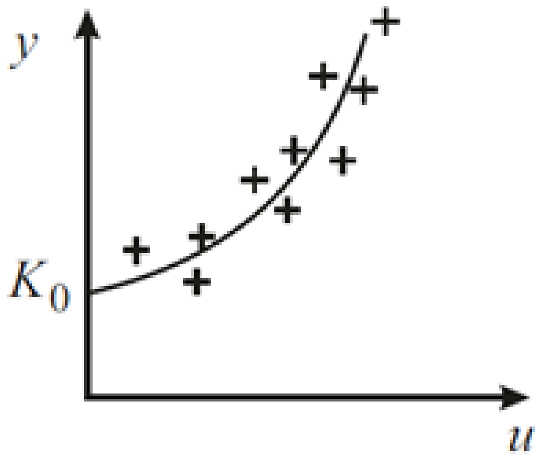

Figure 1.2 : Regression estimation [80].

1.1.2.3 Artificial neural networks

In a comprehensive identification approach, emphasis is placed on methods that are broadly applicable without requiring special experience of the system progress itself. ANNs meet these criteria by mathematically formulating neurons to emulate biological neuron behavior. Through interconnected networks, ANNs describe relationships between input and output signals, with adaptable parameters necessitating training through measured input and output data. This poses a standard system identification challenge. ANNs, acting as inclusive predictors in terms of nonlinearity, offer an alternative to multinominous approximations, showcasing their strength in requiring minimal prior knowledge about the process structure. They excel in providing consistent treatment for both single-input and multi-input model processes, particularly in nonlinear system identification using supervised learning to approximate relationships accurately [80].

1.2 Purpose of Thesis

This study has several goals in temrs of engine modeling and control area. Here are the main output goals of this study:

- Modeling diesel engine using different type of Machine Learning techniques with experimental data. How to collect data from dyno (setup) or ship under way.

- Describe mathematical and practical background of ML techniques that are available for ‘diesel engine modeling’ purpose (supervised etc. from general to specific point).
- Comparing techniques in between; being baseline for the new users in this manner.Try new techniques since there is enoug data.
- Offering new usage area; Real time testing (hardware in the loop).
- Interaction with control; favor to emission legislations (refer to Marpol or Euro 7), fuel consumption and performance. Analyzing performance parameters and offer the techniques to improve them.

1.3 Literature Review

Diesel engine modeling holds immense importance due to its ability to provide valuable insights into the complex dynamics and behavior of marine diesel engines. By simulating the engine's performance under various operating conditions, modeling allows engineers to optimize engine design, control strategies, and emission management systems. It enables a deeper understanding of combustion processes, heat transfer phenomena, and pollutant formation mechanisms, aiding in the development of more efficient and environmentally friendly engines.

One of the key advantages of diesel engine modeling is the significant reduction in time and cost associated with experimental testing. Instead of relying solely on expensive and time-consuming physical tests, modeling offers a virtual platform to explore and evaluate different engine configurations, control algorithms, and parameter settings. This enables engineers to efficiently investigate a wide range of scenarios, leading to faster and more cost-effective engine development cycles. Moreover, diesel engine modeling facilitates the analysis of transient behavior and dynamic response, allowing for the prediction and mitigation of potential issues such as knocking, combustion instabilities, and emissions fluctuations. It offers a means to optimize key engine control features such as speed, torque (injection), and rail pressure, as well as external controllers like exhaust gas recirculation, selective catalytic reduction, and variable geometry turbocharging. By employing machine learning techniques within the modeling framework, it becomes possible to overcome nonlinear engine behavior, improve fuel consumption, and enhance performance criteria while complying with stringent emission regulations.

In the realm of automotive engineering, the modeling of marine diesel engines stands as a pivotal undertaking, holding the key to both enhanced performance and reduced emissions. This exploration delves into the multifaceted landscape of engine modeling, where the convergence of traditional methods and cutting-edge machine learning techniques becomes imperative. Understanding and accurately representing the dynamics of marine diesel engines not only facilitates control and calibration but also emerges as a crucial factor in addressing the ever-growing concerns surrounding performance and emissions. This literature review navigates through the evolution of engine modeling, shedding light on the advantages that lie within its core.

Various engine modeling techniques are employed, ranging from physical models that primarily depict engine mechanics to mathematical models, and more contemporary data-driven models that involve manipulating mathematical parameters based on experimental data. As a base of experimental modeling, different identification methodologies are implemented thruough diesel engines [30] [37] [38] [50] [51] and marine diesel engines [54] [60] [61] [62] specific. Zambrano et al. focuses on NOx reduction by the help of selective catalyst [37]. Experimental data from a Euro VI standard transient test are utilized, including real feedbacks of NOx, urea, inlet temperature, and exhaust flow from related sensors and calculations. The paper employs a Hammerstein-Wiener model, achieving the best estimation for the identification data set and validation dataset separately. MVEM is employed by Theotokatos et al. utilize the Mean Value Engine Model (MVEM) to predict parameters of two-stroke marine engines, considering injection timing and turbine area settings. Engine parameters are mapped using a zero-dimensional (0-D) model, and both 0-D and MVEM models are developed in MATLAB/Simulink. Validation against shop trial data ensures accuracy [54]. The 0-D model is employed for parametric emulation, varying injection timing and turbine area. Results show estimation ability without significantly intricacy increase or execution period, making the proposed extension suitable for engine performance estimation overcoming MVEM restrictions [54]. As another numerical method, Altosole et al. presents a model for a ship diesel engine with turbocharger designed for real-time ship maneuver simulation. The model utilizes a filling and emptying strategy for specific engine elements, while the cylinder emulation relies on a collection of five-dimensional numerical matrices created through a conventional thermodynamic model. This novel approach significantly reduces the transient computation time, allowing for real-time execution. Numerical results from ship acceleration and deceleration maneuvers demonstrate a remarkable reduction in simulation running time, making the model suitable for real-time applications [62]. Mrzlijak et al. present a novel quasi-dimensional numerical model for a diesel engine, departing from conventional approaches by directly solving conservation equations for cylinder pressure and zone temperatures, eliminating the need for numerical iterations. The model is successfully validated across operating points. Subsequent modifications enable the simulation of a marine engine, with the logic of the simulation model remaining unchanged. Comparisons between the simulation results and test bench feedbacks for the two-stroke engine exhibit good agreement, showcasing the accuracy of the developed quasi-dimensional model in predicting operational parameters for both stroke type of diesel engines [61].

With the development of data collection and processing tools, data driven modeling methods and software tools that facilitate the application of these methods, the use and application of data driven models, which will eliminate the uncertainty of nonlinearity, has become widespread. The most well-known of these methods, which may differ due to data type, the number of data, the quality of the data, the type of output to be analyzed, and the application of the model to be used, are regression-based methods and neural networks for diesel engine modeling. As a continuation of these methodologies, deep learning methods and time-series modeling methods have also been actively used recently. Venkatesh et al. delves into the realm of engine testing data and the potential of machine learning for predicting emission characteristics. Linear Regression Algorithm, implemented through the Regression Learner Application in MATLAB, is employed to build a prediction model. The model undergoes validation and comparison with empirical testing data, showcasing minimal errors including MSE, RMSE, R-squared and MAE errors. The validated model proves effective in predicting emission values for various data sets, presenting a time and cost-efficient alternative to repeated testing procedures [32].

Most of regression related models are designed with most effective engine control variables as inputs and most determinative performance and emission parameters as outputs [30] [42] [52] [67] [68]. ANN modeling with different fuel type as input is one of the most useful inputs to observe the change in performance and emission [7] [18] [21] [22] [56] [57] [58] [64] [65] [66]. As BP example for different fuel type usage, Uslu et al. focuses on assessing the productivity and exhaust emissions of a single-cylinder diesel engine oiled with blends of diethyl ether (DEE) and diesel fuel. The data is obtained by running the engine with various mixtures of pure diesel and DEE at different conditions as loads and speeds, serving as training and test data for the ANN model. The ANN model with BPA is designed with performance parameters as brake specific fuel consumption and thermal efficiency, emission parameters as smoke, HCs, NOs and COs, as output variables, and engine load and speed, and blend ratio as input variables. A training ANN is developed by 75% of the experiments, and its performance is evaluated by comparing it with the test data from the remaining 25% of the dataset. The results indicate that the ANN model successfully predicts emissions and performance, achieving a regression coefficient higher than 0.96 [7]. Another BP ANN is developed by Jaliliantabar et al. that takes three main inputs: engine load, engine speed and the percentage of waste cooking oil produced biodiesel. In the end with the successful ANN, the usage of biodiesel in the diesel engine leads to a reduction in most emissions, as observed in the study [18]. Similarly, Shivakumar et al. investigates the effect of injection perioding on the emission and performance output of a waste cooking oil produced biodisel fueled diesel engine. Experiments were conducted at variable injection timings by adjusting the advance shim thickness. BP ANN results showed that BTE was lower for both advanced and retarded injection timings compared to normal injection timing. Smoke and unburnt hydrocarbon were succeeded to decrease for advanced injection timings, while NOx increased [58]. Similar methodlogy is also applied to a spark ignition engine by Kiani et al. to estimate brake power and emissions. Experimental data were collected from ethanol-gasoline blended fuel engine at various ethanol percentages. Overall, the ANN proved to be a fast, accurate, and compatible tool for estimating or approximating performance and emissions, especially when numerical and mathematical methods face challenges [65]. Addition to the engine modeling, standart BP ANN algorithm is also applicable in control manner. Song et al. introduces a BP-PID control algorithm for the diesel engine speed governor. This algorithm is designed with robust adapting and learning abilities, allowing it to approach nonlinear continuous functions with high precision. The BP-PID algorithm enables real-time calibration of the parameters of the speed controller. This investigation affirms the benefits of the BP-PID control algorithm in decreasing overshoot, enhancing dynamic characteristics, and withstanding disturbances in diesel engines. Through simulations and experiments covering diverse conditions, including initial, steady, and sudden load changes, consistent results indicate that the BP-PID algorithm effectively meets the transient speed regulation requirements for a stage power station. The algorithm outperforms traditional PID control algorithms, ensuring engine stability [63].

Besides this, feedforward neural networks, which are frequently used together with back propagation, especially in non-linear system modeling [53] [53] [57] [59] [70]. Roy et al. presents the application of a MLP ANN for the generativity and emissions estimation of a single cylinder CRDI engine under different EGR applications. The The developed ANN model demonstrates remarkable conviniency with the real measured data, with high correlation coefficients aroun 0.99 [36]. Combinational model is developed by Sharma et al.for a similar diesel engine running on a blended mixture of Polanga biodiesel and at different injection pressures. Experimental data was collected under constant speed and full load conditions for train and test the ANN. The ANN model, built using the BPA and a MLP, demonstrated excellent predictive capability. It achieved high correlation coefficients (R) of approximately 0.99998 for thermal efficiency and fuel consumption and as well the exhaust temperature, and emissions as NOx, CO and smoke indicating its accuracy in estimating [24]. Same structure is also applied commonly for marine diesel engines [25] [59]. Castresana et al. addresses the importance of identifying incipient propulsion faults in marine engines to prevent marine incidents. To achieve this, ANN, have been explored for their ability to provide fast and accurate predictions. The study simultaneously predicts 35 different parameters on a six-cylinder marine diesel engine, covering a wide range of engine operation points and characterizing the entire engine performance map. The ANN's structure and training process were optimized using 1,000 data samples, and the model was then validated. The results demonstrated that the ANN model maintained an excellent level of accuracy. The MAPE for most parameters were below 8.5%, except for CO and NO2 emissions predictions. For specific systems such as cooling, oil, and exhaust gas, the MAPE values were even lower, below 4.3%. Notably, the calculation time for predicting 35 parameters across 24 testing samples was a mere 0.109 seconds, highlighting the ANN's efficiency and accuracy in predicting multiple outputs throughout the engine's performance map [25].

Depending on the type, number, quality and complexibility of data or nonlinearity of the modeled system, all modeling techniques can be compared within themselves or derived in a combined way to improve the data driven modeling estimation accuracy [13] [14] [33] [49]. As a first example of standart comparison, the predictive capabilities of linear regression and ANN modeling are explored by Tosun et al. for a naturally aspirated diesel engine. The models aim to forecast engine performance metrics, such as torque and exhaust emissions, including NOx and CO. BP algorithm is employed for the neural networks in multi-layered feedforward networks. Input parameters encompass engine speed and fuel specs, including cetane number, lower value of heating and density. Results indicate that the ANN outperforms the linear regression model, providing more accurate predictions for the desired parameters [33].

ANN methods can branch into different methods, where data processing and computational techniques may differ. As with other machine learning techniques, it can be supported by a number of supporters and combined algorithms [16] [17] [20] [23]. An ANN model that optimized through Response Surface Methodology (RSM) is developed by Aydin et al. to estimate engine performance outputs according to the biodiesel ratio, engine load and pressure of injection. The MLP network illustrates the correlations between input and output factors. RSM is applied to determine the optimal engine operational variables that decrease BSFC, exhaust gas temperature and emissions and increase thermal efficiency in the meanwhile. The results indicate that the ANN effectively models exhaust emissions and productivity parameters with R-squared metric ranging from 0.8663 to 0.9858 [20]. Schürholz et al. employs recurrent neural networks (RNNs) to model the SI Engine aftertreatment system. The study compares various network architectures based on their MSE performances. The findings reveal that physically inspired architectures outperform naive architectures developed without knowledge of the physical system. The best-performing model is evaluated using quantiles of the absolute error [72].

Beside neural networks, different machine learning approaches (vector machines, regression trees, deep networks, time-series identification methods), independent of neural networks, are also widely used efficiently within the scope of engine modeling [9] [11] [12] [34] [35]. In developing an efficient model for a medium-duty diesel engine, Norouzi et al. utilize an SVM that aims to streamline a 34-feature model, resulting in two models: a high-order model with 29 features for NOx and 20 for break mean effective pressure, and a simplified low-order model with 9 features for NOx and 6 for break mean effective pressure. Integrated into a nonlinear control-oriented model, both are validated experimentally using an electrochemical NOx sensor. Comparative analysis with a conventional artificial neural network (ANN) shows promising results for SVM—faster training times (5–14 times) and greater accuracy. Assessment of dynamic behavior and transient responses affirms the high accuracy of the high-order model and satisfactory accuracy of the low-order model, suggesting the former as a precise virtual plant and the latter suitable for model-based controller design. [35]. Also in another comparison study for marine diesel engines, Jeon et al. aims to create the accurate regression model, experimented with different configurations of hidden layers, neurons, and activation functions within the BP ANN optimized with the Levenberg Marquardt optimization and demonstrated that the ANN-based regression model outperformed other techniques like SVMs and polynomial regression in terms of both efficiency and accuracy in predicting fuel consumption for the ship's main engine. This highlights the potential of big data analysis and ANN in optimizing ship maintenance, operational efficiency, and equipment life management for smart ships [23]. To address artificial neural network (ANN) drawbacks such as susceptibility to multiple local minima, user responsibility in selecting optimal network structures, the need for extensive training data, and the risk of overfitting, Wong et al. proposes the use of RVM, for estimating engine performance. RVM's capability to achieve a global optimal solution enables training with a minimal dataset. Scarce data number of engine load, engine speed and cooling temperature are taken into consideration as inputs while NOx, CO and fuel consumption are outputs. Results of RVM model demonstrate satisfactory accuracy even with limited training data, and the model's performance is compared favorably to typical ANN approximation [34].

Time series prediction methods with the time base collected data generally, is also implemented for engine modeling [5] [8] [27] [29] [19] [39] [40] [41]. Maass et al. investigates the utilization of NLARX to predict NOx emissions in heavy-duty diesel engines. Two experiments, incorporating a non road transient cycle (NRTC) and diverse engine operation modes with calibrations, are conducted. The datasets undergo pre-processing, including normalization, and are split into training and validation sets. The chosen NLARX model, implemented with MATLAB Neural Network Toolbox algorithms, undergoes teacher-forced training, showing promising performance during training. The subsequent validation phase reinforces the NLARX model's potential effectiveness in predicting NOx emissions. [39]. Yu Mingxin et al. presents an approach to model diesel engines using various configurations of recurrent neural networks (RNNs). Real data from a physical diesel generator set (DGS) is employed to identify and estimate the mathematical model. Experimental findings showcase the model's accuracy in replicating diesel engine output characteristics, including rotational speed and rack displacement, across diverse electrical power loads [5]. Mahla et al. investigates the viability of biomass-derived biogas as an alternative and environmentally friendly energy source compared to fossil diesel fuel. The study employs an ARIMA model for forecasting emissions and performance characteristics. Evaluation metrics such as Bayesian information criterion (BIC), R^2 and RMSE are utilized to assess the accuracy of the ARIMA models. Experimental results indicate lower NOx and smoke for all operating loads, while CO, CO2, and HC are increasing in comparison of diesel counterparts [27].

Deep neural networks as mathematically improved current type of neural networks are also compatible with nonlinear systems such as engine. Hainan Zheng et al. introduces a novel approach using deep neural networks and virtual sample generation technology for modeling marine diesel engine performance. The model utilizes four input parameters: power, oil temperature, speed and pressure, and assesses engine status using vibration, noise and fuel consumption. Small sample experiments are conducted under various conditions, and the experimental data is augmented through virtual sample generation. Experimental validation shows that the model's overall prediction accuracy exceeds 93%, with power playing a remarkable role in speed and brake specific fuel consumption being crucial for vibration and noise, with specific weightings [1]. Deep Kernel Learning (DKL), which combines deep neural network (DNN) and Gaussian process (GP) techniques, is applied by Yu et al. to compression ignition engine emissions and compared with other surrogate models. These surrogate models, a category of computationally efficient alternatives to physics-based models, include a brief discussion of High-Dimensional Model Representation (HDMR) for benchmarking. The research involves the analysis of a dataset obtained from a compression ignition engine, focusing on soot and NOx emissions. Hyperparameter selection for DKL, encompassing network structure, kernel, and learning parameters, is determined through a combination of quasi-random global search and grid optimization. The evaluation considers the RMSE of predictions and computational costs for DKL, HDMR, plain DNNs and plain GPs. The results highlight DKL's superior performance in RMSE predictions while maintaining reasonable computational costs, with DKL predictions closely aligning with experimental emissions data [4].

Beyond theoretical frameworks, the application of modeling techniques extends to practical realms. Machine learning methodology highlights the diverse usage areas, encompassing calibration, control, and Hardware in the Loop (HIL) studies, providing a holistic perspective on the real-world implications of engine modeling [2] [3] [9] [12] [15] [26] [28] [35] [51] [63] [69] [71] [73]. In a calibration manner for different engine type as spark ignition, Malikopoulos et al. presents an approximation which transforms the engine into an autonomous system proper to real-time self-learning for its entire operating range while a vehicle is in motion. The research establishes a foundational theoretical framework by treating engine operation as a stochastic process and introduces the predictive optimal stochastic learning algorithm. This algorithm forecasts the ideal relationship between engine control parameters and various operating conditions, both transient and steady-state based on observed engine output data. As the Spark Ignition (SI) engine model operates, it incrementally adapts to the driver's typical driving behavior, learning and optimizing spark ignition settings [3]. In a control-oriented investigation, Papadimitriou et al. introduces a structured method for transforming a highly suitable engine model into a fast-running counterpart. The approach involves replacing computationally expensive components with simpler ones under specific assumptions, significantly boosting computation speed while preserving the engine's physical representation to a wide scope. The result is well-suited for swift simulations and maintains usability and updatability in later development stages. The key element of the method entails calibrating the fast-running components using automatically selected neural networks. Demonstrative examples highlight the methodology, revealing a substantial improve in computation speed with well enough accuracy [71][73]. Papadimitriou et al. also introduces an innovative method for real-time engine modeling, diverging from conventional system-level modeling practices. The proposed approach blends physical and system domain solutions for real-time applications as HiL. Tailoring each subsystem with a chosen solution—be it physical, map-based, or a hybrid—depends on computational power and the desired model detail. These models, adaptable for HiL simulations, offer reusability with potential updates. The method allows for a various level of detail, accommodating look up tables for torque and exhaust temperature, as well as more intricate models proper for the estimation cylinder pressure at as part of crank angle resolution. This adaptability ensures alignment with the ongoing advancements in computational power. [71].

Due to their data-centric investigations and adaptability to diverse systems and applications, machine learning methods are extensively employed in engine modeling beyond just diesel engines and marine diesel engines [3] [17] [28] [43] [44] [45] [46] [47] [69] [72]. Pogorelov et al. proposes an engineering method for constructing recurrent neural networks (RNN) and identifying mathematical models for gas turbine engines using real data. The process encompasses designing the gas turbine model in the form of neural networks, implementing the learning algorithm, and defining the network structure. The method was validated through modeling and experimental investigation, including testing and debugging on a HiL test bench with a full authority digital engine control closed-loop control for start-up, ground, and flight modes [69].

Considering another type of SI engine as rotary type engine, Shi et al. aimed to enhance the engine management system of a hydrogen added Wankel engine to meet stringent emissions regulations and improve performance. Engine calibration tests with varying excess air ratios, ignition timing, and hydrogen enrichment were conducted, and the experimental data were utilized to create multi-objective regression models. Three methods, ANN, quadratic polynomial and SVM were employed for modeling. For ANN, the impact of hidden layer node count on regression performance was discussed, and a genetic algorithm optimized the weight values. For SVM, the influence of kernel function and optimization methods on regression performance were explored. SVM demonstrated the best fitting results, with optimal R2 values for the outputs as brake thermal efficiency, and emissions like HC, NO and CO [45]. In another study Gaussian process regression (GPR) is located by Wang et al. in comparison of the ANN and SVM instead of quadratic polynomial.The study examined the effect of different input parameters on model performance, concluding that using speed, manifold absolute pressure, and air fuel ratio yielded the best results. The study compared the generalization capabilities of Machine Learning (ML) models on both interpolative and extrapolative datasets, highlighting GPR as outperforming others, particularly in situations with limited data. GPR showcased simplicity in training compared to ANN and SVM, producing smooth and accurate response surfaces [46].

Area of interest for this study, machine larning methods are compared with each other and performance analysis can be made according to their suitability for engine modeling and data processing processes in the literature. Comparisons and combinations can be improved as the methodologies and the implementation of machine learning techniques differ [10] [29]. Mohammad et al. proposes a hybrid approach that combines the strengths of both physical and data-driven modeling, creating a "grey box" model for predicting exhaust emissions from a commercial vehicle diesel engine. The physical investigation of internal engine processes is used to determine key combustion characteristics that influence NOx, CO, HC, and soot emissions. Using these physically modeled inputs, machine learning models like SVM and feedforward neural networks (FFNN) are developed for emission prediction. These models are trained on data from a diesel engine, rigorously validated against various hyperparameters and network structures, and compared across 772 different operating points. The results reveal that integrating physically modeled inputs significantly enhances the performance of FFNN and SVM. For instance, HC and soot modeling with feedforward neural networks see an improvement of approximately 20% and 10% in root mean square error (RMSE) on test data, respectively. Support vector machines benefit the most in CO and soot modeling, with a reduction of 30% and 20% in RMSE on test data, respectively. Furthermore, the NOx model, initially trained on low-load data, demonstrates a notable increase in its coefficient of determination when applied to high-load data, indicating enhanced predictive performance [6].

This study aims to discover most popular used machine learning methodologies and evaluate them in terms of marine diesel engine modeling. Main target is to provide permanent overview that contains the implementation of main machine learning techniques on engine modeling for improving performance and emission investigations [13]. In a pivotal reference for this study, Vorkapic et al. establish a machine learning model to monitor crucial operating parameters and predict fuel consumption in a two marine engine. Various ML algorithms, including LR, MLP, SVM, and RF, are tested within the modeling framework. To enhance prediction accuracy, the model's verification and result analysis are conducted, and the best algorithm is chosen based on standard evaluation metrics like RMSE and RAE. Experimental outcomes indicate that, through a judicious combination and processing of pertinent sensor data, SVM and RF come to the forefront in case of the comparions with other techniques. In another significant study [48], advanced ML methodologies, including SVMs with least square, RVM, basic ELMs, and kernel-based ELM, are explored to model diesel engine performance. Wong et al. collected experimental data for model training and verification, utilizing 24 sample datasets constrained by experimental conditions. To address data scarcity, a six-fold cross-validation approach was employed. Some datasets exhibited exponential growth, impacting prediction accuracy, and a logarithmic transformation of dependent variables was applied for data pre-processing [48]. To select hyperparameters for kernel-based ELM, a hybrid approach of leave-one-out cross-validation and Bayesian inference was proposed. A comprehensive comparison with traditional ANN models BPNN and RBFNN considered complication of time and space, and estimation accuracy. The evaluation results revealed that, with logarithmic transformation and hybrid inference, kernel-based ELM surpassed basic ELM, RVM, LS-SVM, BPNN, and RBFNN in terms of both prediction accuracy and training time [48].

Sujesh et al. provides an exploratory review of the efforts made in the last decade to improve the effectiveness and capabilities of diesel engines. The review covers the evolution of performance improvement methods, different modeling approaches and advanced metrics employed to assess the performance of diesel engines. It then delves into the use of artificial intelligence methods to achieve performance improvements. The review highlights a significant challenge in optimizing diesel engine performance: dealing with noisy experimental data, ensuring robustness, handling imprecise data, and addressing temporal variations in fitness models. As these challenges persist in optimization algorithms and diesel engine modeling, there is substantial room for further research and advancement in this field. Ultimately, studies such as engine modeling techniques and relevant comparisons are investigated in order to facilitate engine performance and emission analysis and to open space for control algorithms. Therefore, this study is considered as another important literature reference [26].

Turkson et al. delve into the calibration perspective and explore the potential of utilizing trained neural networks in conjunction with design of experiments (DoE) techniques for engine calibration. Artificial neural networks are underscored as a preferred choice over alternative data-driven modeling techniques due to the increasing stringency of emission regulations. They stand out in meeting the demands of engine calibration, addressing challenges like the curse of dimensionality, optimizing model parameters to prevent overfitting, and facilitating automated online optimization during calibration, thereby minimizing the need for user intervention. The review comprehensively examines different implementations of neural networks in spark-ignition engine calibration [28].

This research serves as a literature review focusing on the application of machine learning methods in the context of low-speed marine diesel engines. These engines, anticipated to have relatively limited usage but facing stringent short-term restrictions, prompted an exploration into the literature. The objective is to categorize methods based on criteria such as data type, quantity, diversity, modeling mathematics, and model complexity. Moreover, the plan involves a comparative analysis, particularly emphasizing the comparison of time-series nonlinear autoregressive methods and their derivatives with neural network methods. Notably, this comparative study aims to contribute insights into the modeling and control perspectives of diesel and marine diesel engines. It involves assessing the engine's structure, operational needs, benefits, and conducting a detailed examination of both engine performance and emission constraints, particularly those stipulated in the MARPOL regulations. The study delves into environmental factors, theoretical and practical applications of data-driven models, as well as the stages of data collection and processing. Additionally, it examines model creation tools and underscores the advantages of automating these models for sustained long-term use.

2. DIESEL ENGINE PERFORMANCE

2.1 General Overview

Diesel engines are internal combustion engines widely used in various applications, known for their efficiency and durability. They operate by compressing air and injecting fuel, leading to spontaneous ignition. The diesel cycle, named after inventor Rudolf Diesel, is the foundation of their operation. Since Rudolf Diesel's early designs in the late 19th century, diesel engines have undergone significant improvements. Advances include enhanced fuel injection systems, turbocharging, electronic control systems, and materials technology, contributing to increased efficiency, power, and reduced emissions [84].

Diesel engines, recognized for their efficiency and reliability, stand as stalwarts in the realm of internal combustion engines. Originating from the pioneering work of Rudolf Diesel in the late 19th century, these engines have undergone a remarkable journey of evolution and refinement. The historical trajectory reveals a continuous quest for enhanced performance, fuel efficiency, and environmental responsibility. Noteworthy advancements in fuel injection systems, turbocharging technologies, and electronic control mechanisms have propelled diesel engines to the forefront of various industries. Literature underscores this journey, with seminal works define the diesel cycle and its subsequent improvements.

The historical narrative intertwines with the present, where diesel engines, through their sustained ingenuity, continue to power a myriad of applications ranging from transportation to industrial machinery and marine propulsion. As we delve into the intricacies of diesel engines, it becomes evident that their story is not just one of mechanical innovation but a dynamic response to the evolving needs of a technologically advancing society. It offers a means to optimize key engine control features such as speed, torque (injection), and rail pressure, as well as external controllers like EGR, selective catalytic reduction (SCR), and VGT. By employing machine learning techniques within the modeling framework, it becomes possible to overcome nonlinear engine behavior, improve fuel consumption, and enhance performance criteria while complying with stringent emission regulations [85].

Diesel engines play a crucial role in transportation and industry worldwide, and their prevalence has predominantly grown due to heightened demands for fuel efficiency. Diesel engines offer notable advantages over petrol engines, particularly in terms of fuel efficiency and robust durability. Unlike petrol engines, diesel engines operate by compressing air to high pressure and temperature within the piston. The injection of fuel into this compressed air leads to auto-ignition, releasing chemical energy. The ensuing combustion gases expand, performing work on the piston before being expelled. Unlike spark-ignition engines, where power output is controlled by throttling air intake, diesel engines regulate power output (or load) by adjusting the amount of injected fuel. This absence of part-load throttling, coupled with a higher compression ratio, results in diesel engines showcasing superior efficiency compared to spark-ignition engines. However, the lack of throttling leads to poor air utilization in diesel engines [86] (Figure 2.1).

Figure 2.1 : Four stroke diesel engines [83].

Diesel engines display various categorizations based on their cycle type (two-stroke or four-stroke), injection method (direct or indirect), and aspiration (naturally-aspirated or supercharged). Their classification further extends to specific service needs, including automotive, industrial, rail, or marine engines. This study specifically concentrates on constructing a model for estimating performance of marine diesel engines with direct injection but also investigates on other type of engines. The focus extends to service classifications encompassing light to heavy-duty automotive and small to medium industrial applications. Diesel engines, renowned for their efficiency and fuel economy, dominate various sectors, including fixed installations, automobiles, heavy vehicles, agriculture machines, marine industry and railway vehicles. These engines, produced in inline or V-configuration units, excel in turbocharger or supercharger aspiration, avoiding issues like knocking common in gasoline engines. When assessing diesel-engine applications, crucial features such as engine power, safety, cost, economy, reliability, and environmental compatibility play a significant role. Their relative importance varies based on the application type, influencing engine design accordingly [82].

In the realm of specific applications, car engines have made substantial progress in torque production and smooth operation, integrating into executive and luxury car markets. Heavy goods vehicles prioritize economy and use exclusively direct-injection (DI) diesel engines. Construction and agricultural machinery focus on economy, durability, and reliability. Railway locomotives and marine diesel engines prioritize continuous-duty performance, adapting to specific challenges such as poorer quality diesel fuel. Additionally, some engines are designed for multi-fuel capability for specialized applications, though their current significance is limited due to challenges in meeting emissions and performance standards [81].

2.2 Working Principles

Considering working principle, diesel engines, renowned for their efficiency and widespread applications, operate on a distinctive combustion principle that sets them apart from other internal combustion engines. At the heart of diesel engines lies a unique working principle that emphasizes fuel efficiency and durability, making them a cornerstone in various industries. The fundamental working principle of diesel engines involves the compression ignition of fuel, a process that distinguishes them from gasoline engines and influences their notable efficiency. Understanding the stroke structures in diesel engines is crucial to grasp their operational dynamics, where each phase in the engine cycle contributes to the overall efficiency and power output.

The diesel engine functions as a compression ignition engine, with intense compression of air in the combustion chamber leading to elevated temperatures. This enables auto-ignition of diesel fuel upon injection, converting its chemical energy into mechanical force. Known for efficiency exceeding 50%, low fuel consumption, and low-emission exhaust, diesel engines can be adapted with turbochargers or superchargers for enhanced power and efficiency. They utilize features like pre-injection for quieter operation. To address NOx emissions, exhaust gas recirculation and cooling methods are employed, showcasing the engine's versatility and environmental considerations. Diesel engines exhibit versatility, capable of functioning as either two-stroke or four-stroke engines, with four-stroke designs being prevalent in motor vehicles. Within a diesel engine, each cylinder undergoes a series of precisely orchestrated strokes, defining its operational cycle. The "reciprocating-piston engine" derives its name from the up-and-down movements of the piston within the cylinder, driven by the combustion of the air/fuel mixture. This reciprocal motion is crucial in converting linear energy into the rotational movement essential for the engine's overall operation. In a four-stroke diesel engine in Figure 2.2, each cycle involves four distinct phases:

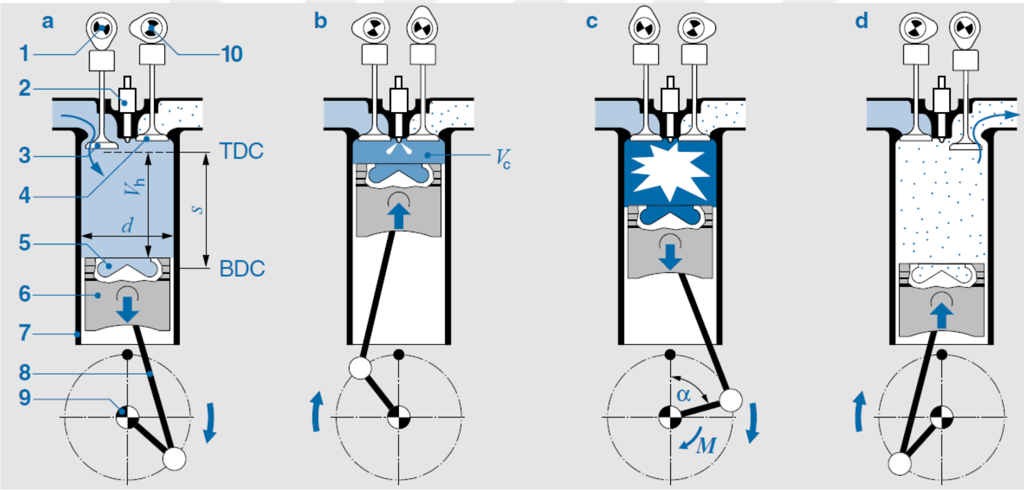

Figure 2.2 : Four stroke diesel engine operation [81].

Induction Stroke: The piston descends, expanding the cylinder's capacity beginning from TDC. The inlet valve opens, enabling unrestricted air intake. At BDC, the cylinder achieves its maximum capacity [81].

Compression Stroke: With closed valves, the piston ascends, compressing air within the cylinder. Compression ratio determines the degree of compression, elevating air temperature. Fuel injection occurs, and at Top Dead Center, the cylinder reaches its smallest capacity [81].

Ignition Stroke: After a brief ignition lag, diesel fuel spontaneously ignites during the compression process. This ignition initiates the working cycle, converting chemical energy into kinetic energy. The resultant pressure forces the piston downward, and the crankshaft translates this energy into torque [81].

Exhaust Stroke: Exhaust valve opens before BDC, releasing the exhaust gas with high pressure and temperature. As the piston ascends, it expels remaining exhaust gases. The exhaust stroke completes two crankshaft revolutions, restarting the four-stroke cycle. This precise sequence in a four-stroke diesel engine highlights its role in efficient energy conversion across diverse applications. [81].

The interconnection between the crankshaft and camshaft involves a toothed belt, timing chain, or gears. In a four-stroke engine, the roational speed ratio of crankshaft to camshaft is 2:1. During the exhaust to induction stroke transition, both valves stay open, termed "valve overlap," purging exhaust gases and cooling the cylinders for enhanced engine efficiency [81] (Figure 2.3).

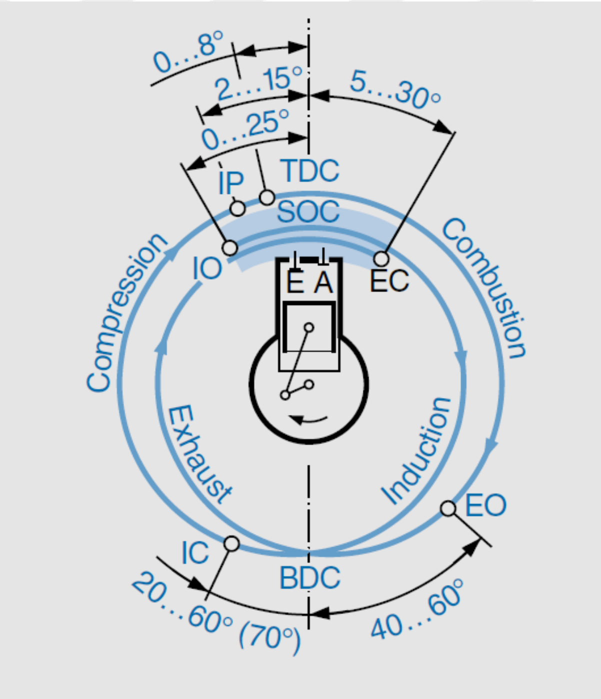

Figure 2.3 : Diagram of valve timing [81].

In small turbocharged diesel engines for cars, the mean pressure can range from 8 to 22 bar, surpassing the levels achieved by gasoline engines, which typically fall between 7 and 11 bar. The engine's design, including factors such as cubic capacity and aspiration method, determines the maximum achievable torque (Mmax).

Engine power (P), indicating work per unit of time, relies on both torque (M) and engine speed (n) (2.1). Figure 2.4 represents engine torque, speed and power relation:

$$P = 2 * \pi * n * M \tag{2.1}$$

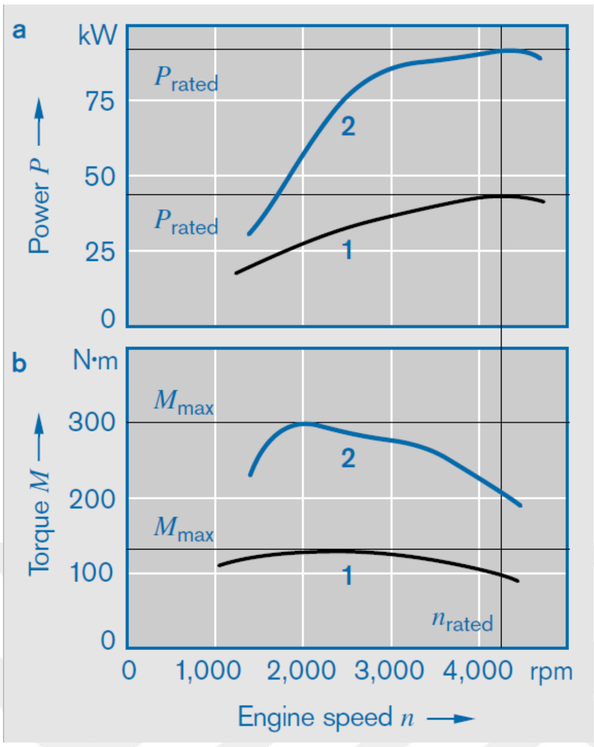

Figure 2.4 : Diesel engine curves (torque, power) [81].

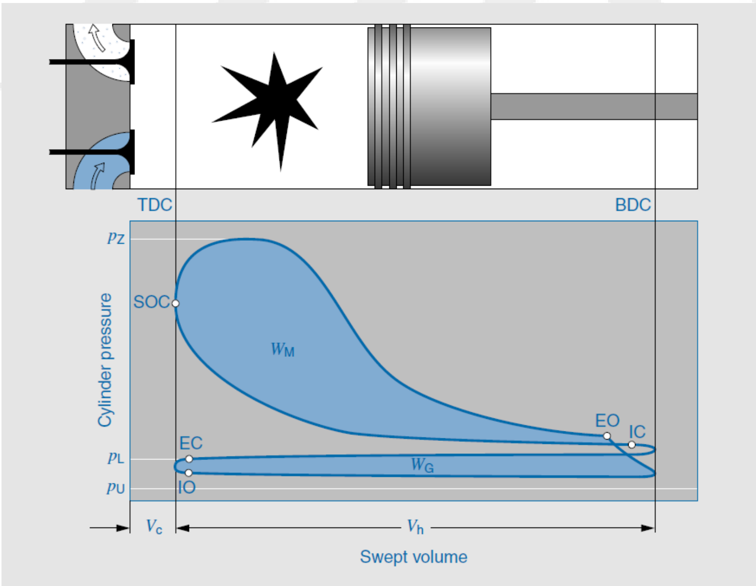

Figure 2.5 : P-V indicator diagram for turbocharged diesel engine [81].

To quantify the work accomplished in the actual process, the pressure curve within the cylinder is gauged and depicted in the p-V chart as shown in Figure 2.5. The region under the upper curve corresponds to the work carried out at the piston. For engines with assisted aspiration, the gas-exchange area (WG) is additionally incorporated, considering that the compressed air supplied by the turbocharger aids in driving the piston downward during the induction stroke. Many operating points witness the turbocharger compensating for losses incurred during gas exchange, contributing positively to the overall work done. Techniques such as representing pressure through the crankshaft angle find application in thermodynamic pressure-curve analysis [81] .

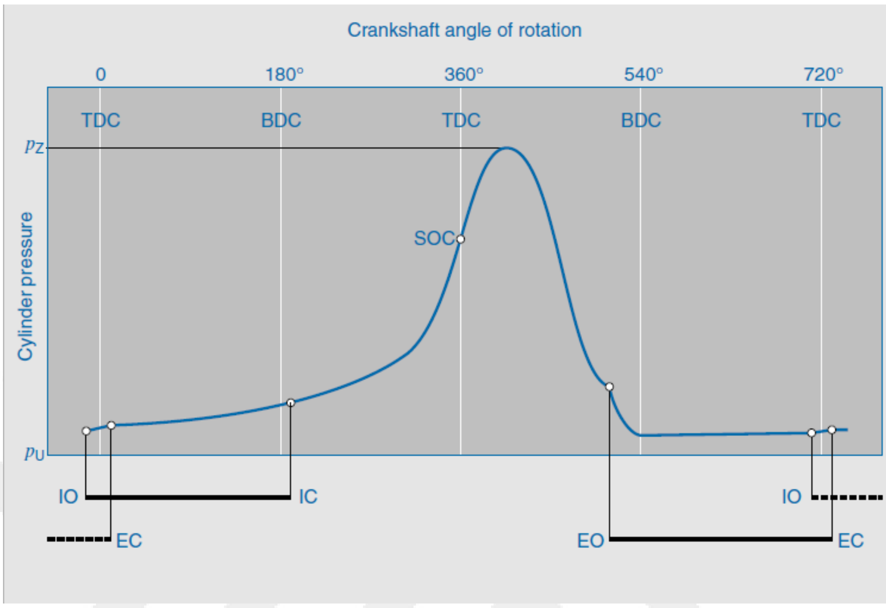

Figure 2.6 : Cylinder pressure and Crankshaft rotation angle diagram [81].

The diesel engine efficiency (ηe) is the ratio of the efficiently suitable work at the crankshaft (We) to the calorific value of the supplied fuel (WB) [81]. It comprises various factors, including (Figure 2.6):

- Thermal Efficiency (ηth): Associated with the Seiliger process, considering heat losses. Diesel engines, with higher compression ratios and excess-air factors, achieve greater efficiency than gasoline engines [81].

- Cycle Factor Efficiency (ηg): Quantifies the work done in the real high-pressure process. Deviations arise from factors like real working gas, heat propagation velocity, position, wall heat loss, and gas-exchange process losses [81].

- Fuel Conversion Factor Efficiency (ηb): Considers losses due to incomplete fuel combustion in the cylinder [81].

- Mechanical Efficiency (ηm): Includes friction and ancillary assembly losses, increasing with engine speed. Frictional losses involve components like pistons, bearings, oil pump, coolant pump, valve-gear, and fuel-injection pump [81].

Considering overall, the efficiency of a diesel engine is a comprehensive measure incorporating various factors that affect both the ideal and real processes.

In a diesel engine, fuel injection is applied into highly compressed air with high temperature, causing spontaneous ignition. Diesel engines, unlike gasoline engines, are not limited by ignition constraints (specific air-fuel ratios λ) due to the non-homogeneous air/fuel mixture. The fuel injection system of diesel engine is vital for managing fuel quantity across different conditions, ensuring precise fuel delivery in terms of amount, timing, pressure, and pattern in the combustion chamber [81].

Controlling the fuel quantity involves accounting for factors like pressure, temperature, and emission constraints, speed and full-load restrictions etc. [81]. Smoke limits are defined by statutory regulations, emphasizing the efficiency of air utilization at full-load smoke limits. Combustion pressure limits, influenced by hard combustion, dictate the permissible injected fuel quantity. Pre-injection is employed to counteract sudden rises in combustion pressure [87] [88].

Exhaust temperature limits are determined by thermal compulsions on engine elements. Engine speed limits are crucial to prevent self-destruction; thus, engine speed limiters or governors are essential. Diesel engines for road vehicles require an infinitely variable engine speed controlled by the driver, while those for machines use a variable-speed governor for specific speed control. Altitude or turbo pressure limits necessitate adjusting the injected fuel quantity based on variations in air pressure at different elevations. Turbocharged engines may require fuel quantity adjustments in dynamic progress to align with lower air flow ratios [81].

2.3 Performance Parameters

Examining fuel consumption in diesel engines across various speeds and loads is crucial. The use of an engine performance map estimates fuel usage throughout the operating cycle. Parameters, both geometric and thermodynamic, play a role in characterizing fuel consumption performance. This section explores these parameters, providing insights for selecting inputs in neural network models. Strategic input choices, based on an understanding of factors influencing diesel engine performance, improve the generalization ability of neural network models, aligning with the study's primary objective [80] [81] [89].

Efficiency, fuel consumption, and exhaust composition in diesel engines are intricately linked to air-fuel mixture preparation. Critical fuel-injection parameters include injection begin, discharge ratio curve, duration, pressure, and injection events. Combustion-process control within the engine significantly reduces emissions and noise. Earlier, until the 1980s, mechanical means controlled fuel injection. Current emission standards demand precise adjustments through electronic control units, considering factors like temperature, speed, load, and altitude. The electronic diesel engine control unit and related functions are widespread, and future measures for emission reduction will be essential [80] [81].

The concept of excess-air factor, denoted by λ (lambda), serves to illustrate how the actual air/fuel mixture differentiation to the stoichiometric ratio. In detail (2.2):

$$\lambda = \frac{\text{Air mass}}{(\text{ Stoichiometric ratio x mass of fuel})} \tag{2.2}$$

Here's what the values of λ signify:

$\lambda = 1$: Enough charge air mass equals for complete fuel combustion.

$\lambda < 1$: Low air intake mass; indicating a rich mixture.

$\lambda > 1$: Higher air intake mass; signifying a lean mixture.

This parameter is crucial in understanding and controlling the combustion process, allowing adjustments to achieve optimal conditions for combustion efficiency and emission control. Diesel engines, unlike gasoline engines, require an overall excess of air to avoid the formation of sooty combustion areas. Lambda levels, denoting the ratio of total air and fuel masses in the cylinder, play a crucial role in controlling auto-ignition and pollutant production [89].

Turbocharged diesel engines typically maintain lambda levels between $\lambda = 1.15$ and $\lambda = 2.0$ at full load, rising to $\lambda > 10$ during idling and no-load conditions. These excess-air factors vary spatially and significantly influence auto-ignition and pollutant generation. Higher injection pressures promote improved fuel atomization and scattering in the cylinder. To maximize power from a given engine capacity while minimizing weight and cost, diesel engines aim to run with the lowest possible excess air at high loads. However, insufficient excess air can increase soot emissions, necessitating precise fuel injection control based on available air mass and engine speed. Altitude variations, causing lower atmospheric pressures, require adjusting the fuel volume to match the reduced air amount, highlighting the importance of adapting fuel injection to environmental conditions [81] [89].

2.4 Control Perspective

Having established a comprehensive point of view of the fundamental aspects and performance metrics of diesel engines, it is imperative to delve into the intricacies of control algorithms for optimal operational efficiency. Beyond the conventional performance parameters that characterize engine behavior, the realm of engine control involves a meticulous consideration of key variables that play pivotal roles in governing both speed and torque. Parameters such as the start of injection angle, boost pressure, common rail pressure, and injection quantity emerge as focal points in the design of control algorithms, offering a nuanced perspective on engine management. These parameters, when harnessed judiciously, not only contribute to the overall performance of the diesel engine but also serve as critical inputs for the calibration and refinement of control strategies, aiming to enhance the realism and robustness of the modeling process [80].

The intricacies of diesel engine control are orchestrated through a sophisticated array of control functions, each contributing to the overall performance and efficiency of the powertrain. At the core of these control strategies lies torque control, which serves as the linchpin for regulating the engine's power output. Torque control involves the meticulous adjustment of fuel injection and air intake to achieve desired torque levels, ensuring optimal performance under varying load conditions. Injection and air/fuel control further fine-tune the combustion process, influencing efficiency and emissions. Ignition control optimizes the timing of combustion events, enhancing fuel ignition and burn characteristics. Knock control safeguards the engine against potentially damaging detonation, adjusting parameters to mitigate knock events. Air charge control and EGR control fine-tune the composition of the air fuel mix, optimizing combustion efficiency and emissions. This intricate interplay of control functions forms the backbone of a diesel engine's operational strategy, balancing power output, fuel efficiency, and emissions in a dynamic and responsive manner.

The primary responsibility of the engine control system is to observe and regulate all essential operations within an internal combustion engine. A cursory examination reveals several key objectives as generating torque in accordance with the accelerator pedal input, achieving low fuel consumption, ensuring minimal exhaust emissions and noise levels according to regulations and enhancing overall driving performance.

In the context of the overall assembly of the engines, these control functions can be evaluated in different sub-fuctions namely intake, injection, combustion, aftertreatment, cooling systems. The control unit's role extends to each of these subsystems, orchestrating their harmonious interaction to meet the overarching goals of performance, efficiency, and environmental compliance.

A subset of engine subsystems relies on mechanical control, exemplified by mechanisms like camshafts regulating inlet and outlet valve timing and lift in four-stroke engines. Additionally, fuel pressure, oil pressure, and coolant temperature are mechanically controlled through devices such as overpressure relief valves and thermostatic expansion valves. Despite this, the landscape of engine control extends to numerous electronically managed variables, including air and fuel flow, speed, torque and exhaust gas treatment [80] [81]. Due to cost constraints or robustness considerations, certain output variables, like torque and specific emissions, remain unmeasured in mass-produced vehicles. To address this, feedforward structures, also known as open-loop structures, are employed. These structures necessitate the measurement of driver-related variables, such as pedal position, engine speed, air temperature and mass flow etc. to specify feedforward control behaviours on main manipulation variables [80] [81].

The primary components equipped in a diesel engine including a turbocharger are depicted in the figure. In the absence of turbochargers, low pressure air is drawn into the cylinders compared to pressure of atmosphere. However, diesel engines with current technology, integrated with turbochargers to augment torque and power. The air charge is contingent on charging or boost pressure, adjusting by the turbocharger VGT or the opening rate of wastegate. Diesel engines operate with substantial excess air at low loads, expressed by the excess-air factor λ, only converging to 1 at higher loads. This efficiency advantage is attributed to the high compression ratio, low charging losses, and good air supply, particularly at part load.

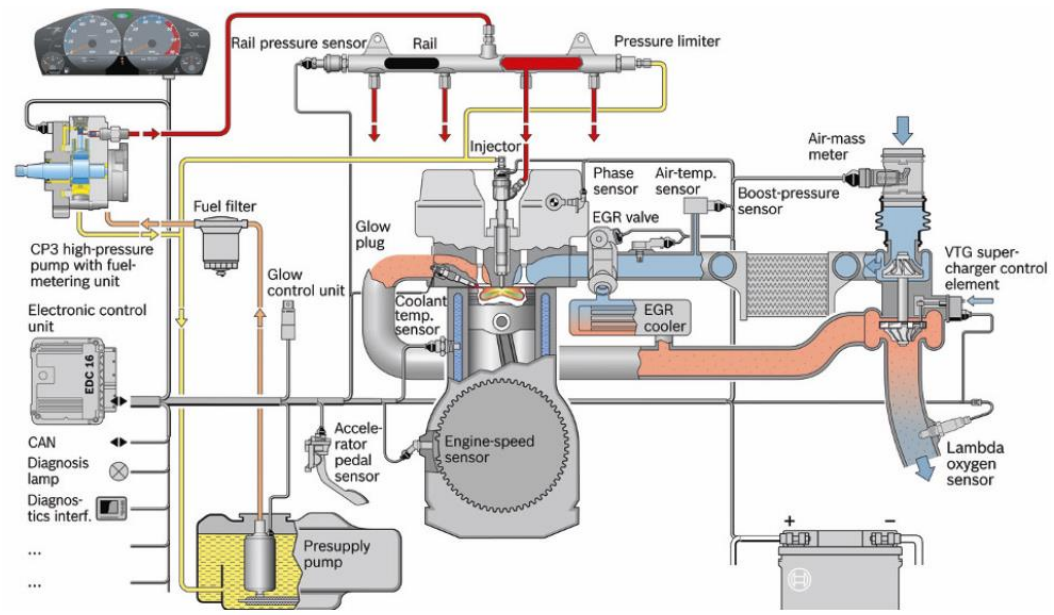

Figure 2.7 : Diesel engine components schematic [80].

Modern diesel engines equipped with a common rail injection system, achieving pressures up to around 2200 bar. Electronic control unit directs injected fuel mass based on the driver's accelerator pedal position. To optimize fuel consumption, decrease NOx, and minimize noise, multiple type of injections occur during pre-, main-, and after-injection pulses. Related schematic is shown in Figure 2.7 and Figure 2.8. The EGR valve indirectly influences air intake system, especially in passenger car diesels [80] [81].

Diesel engines necessitate a speed controller to prevent overspeeding and potential damage. Speed control is also operated during idling different from the normal operating range. Exhaust after-treatment targets the reduction of NOx, HC, CO and particulates. In most passenger car diesel engines, an oxidation catalyst is used to eliminate HC, CO, and some soot. To address NOx emissions, diesel particulate filters (DPF) and NOx storage catalysts or selective catalytic reduction (SCR) are employed.

The schematic structure of diesel control system is presented in Figure. The system employs closed-loop control for air flow, common rail pressure, charging pressure, and, in some cases, exhaust gas after-treatment, supplemented by numerous feedforward control functionalities [80].

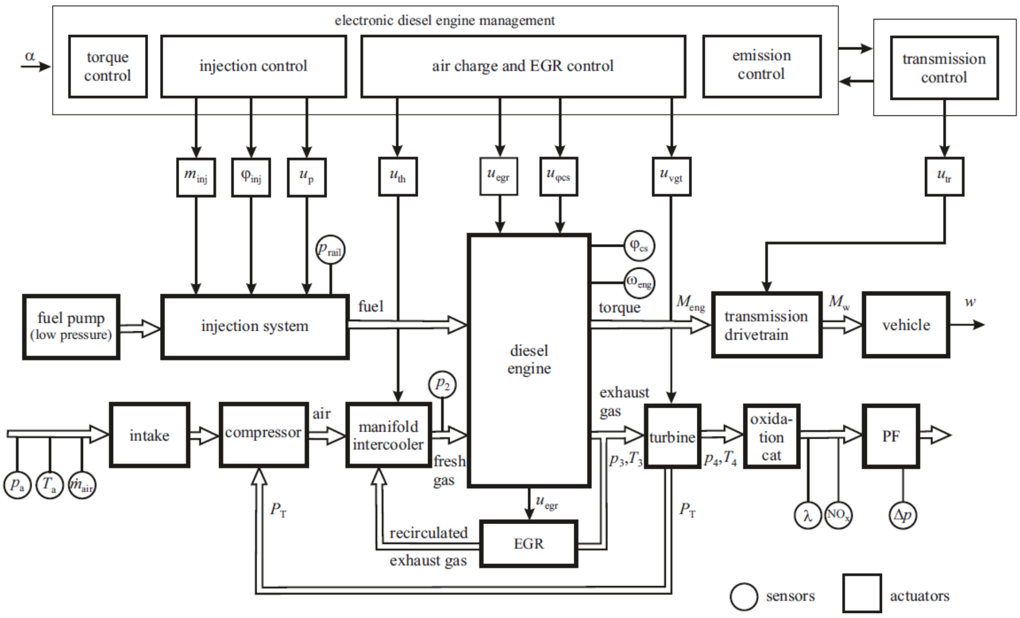

Figure 2.8 : Schematic control diagram of diesel engine [80].

2.5 Marine Diesel Engines

The inception of marine diesel engines dates back to the late 19th century when Rudolf Diesel successfully developed the first practical compression-ignition engine. The marine industry quickly recognized the efficiency and reliability of diesel engines, leading to their widespread adoption for maritime propulsion. Over the years, continuous advancements in design, fuel injection, and materials have propelled marine diesel engines to become the primary power source for various vessels, playing a crucial role in the evolution of maritime transportation [cg, but Pounders is same]. Prominent manufacturers in the marine diesel engine industry include MAN Energy Solutions in Figure 2.9, Wärtsilä, Caterpillar, and Rolls-Royce. For instance, the Wärtsilä RT-flex96C, known for its exceptional power output, is one of the largest and most powerful marine diesel engines, commonly used in large container ships and oil tankers. These brands showcase the diverse range of marine diesel engines, tailored to different vessel types and operational requirements.

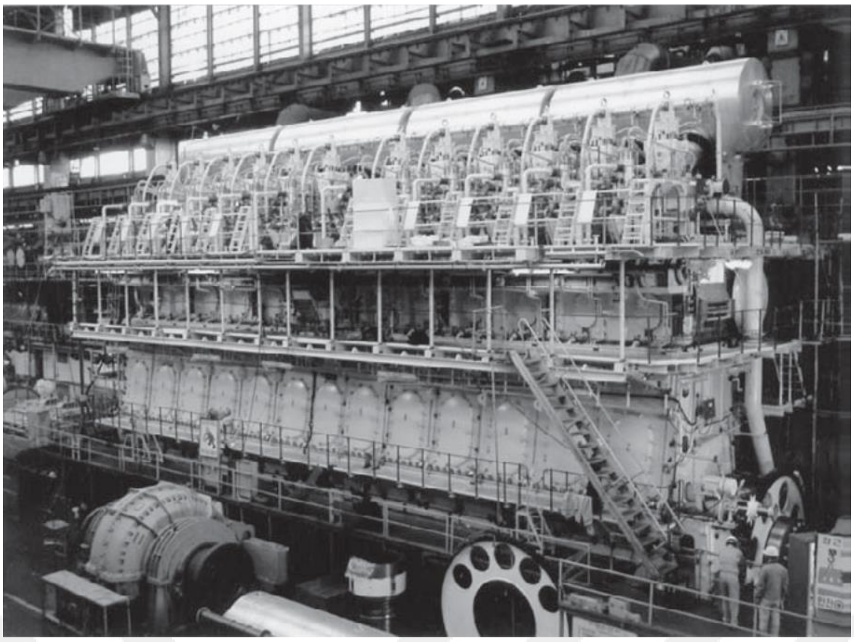

Figure 2.9 : 12-cylinder MAN low speed marine diesel engine [90].

Marine diesel engines share the fundamental principles of internal combustion with their automotive counterparts. The majority of marine engines operate on either the four-stroke or two-stroke cycle. The four-stroke cycle involves intake, compression, power, and exhaust strokes, similar to standard vehicle diesel engines. Two-stroke engines, however, contains the combination of the intake and compression, and power and exhaust strokes. The distinction from vehicle diesel engines lies in the specialization for marine applications, where engines are categorized into high-speed and low-speed types, varying in design, power output, and operational characteristics.

2.5.1 Working principle

In addition to the widespread use of 4-stroke engines in various applications, 2-stroke engines have found prominent utilization, particularly in the marine industry. These engines offer distinct advantages that make them well-suited for maritime propulsion. The efficiency, simplicity, and specific design features of 2-stroke engines align seamlessly with the unique requirements of marine applications. Their notable benefits, such as a higher power-to-weight ratio and a more straightforward mechanical structure, make 2-stroke engines a preferred choice for many marine vessels. The inherent characteristics of these engines, including their ability to generate power with fewer components, contribute to their popularity alongside 4-stroke engines in the dynamic and challenging environment of the open seas. Large marine diesel engines, ranging from 0.4 to 1 meter in bore size, employ the two-stroke cycle.

These low-speed engines, featuring a limited number of cylinders, prove highly suitable for marine propulsion due to their ability to meet the power and speed requirements of ships through straightforward direct-drive configurations. Turbocharging is applied to these engines to attain elevated brake mean effective pressures and specific output. The most substantial among these engines can realize brake fuel conversion efficiencies reaching as high as 54 percent. This accomplishment is attributed to the augmentation of maximum firing pressure to 13 MPa and the optimization of critical engine processes, including fuel injection, combustion, supercharging, and scavenging.

The four-stroke cycle necessitates two revolutions of the crankshaft for each power stroke in every engine cylinder. In pursuit of enhanced power output within a given engine size and a more straightforward valve configuration, the two-stroke cycle was devised. Applicable to both spark ignition and compression ignition engines, this cycle relies on ports in the cylinder liner, manipulated by the piston's motion, to regulate the exhaust outflow and intake of a fresh charge. These events occur as the piston nears Bottom Center (BC). The two strokes are as follows: first, a compression stroke that initiates combustion near Top Center (TC) after closing the fresh charge transfer ports and exhaust ports, compressing the cylinder's contents as the piston ascends and drawing fresh charge through the inlet Reed valve. Second, a power or expansion stroke akin to the four-stroke cycle until the piston approaches BC, revealing the exhaust and transfer ports. During this process, most burnt gases exit through exhaust blowdown, and when the transfer ports open, the compressed fresh charge in the crankcase flows into the cylinder. The piston and ports are strategically designed to redirect the incoming charge away from the exhaust ports, ensuring effective scavenging of residual burned gases in the cylinder. Each engine cycle, inclusive of one power stroke, concludes in a single revolution of the crankshaft. Despite this, it proves challenging to entirely fill the displaced volume with a fresh charge, leading to some of the mixture exiting the cylinder directly during scavenging [86].

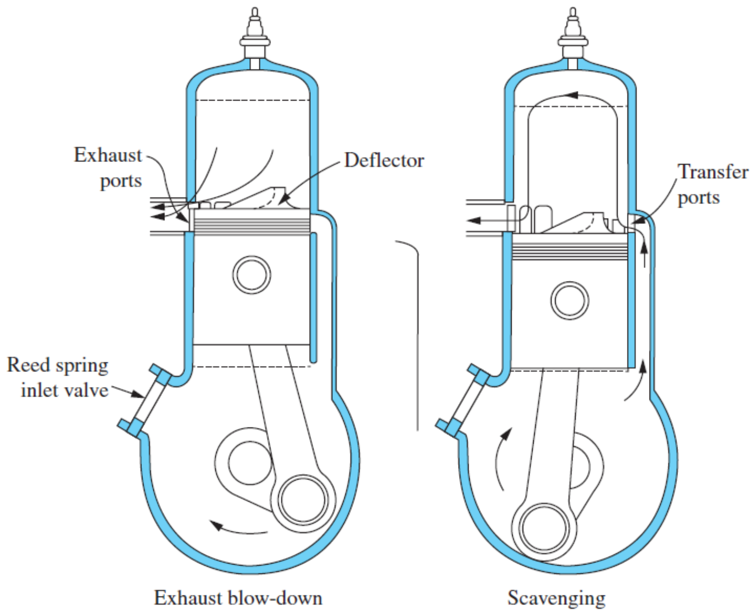

Figure 2.10 : The two-stroke operating cycle of diesel engine [86].

As its shown at the Figure 2.10, the sequence of actions in a standard two-stroke cycle, a process accomplished in a single revolution of the crankshaft, as implied by its name. Two-stroke engines commonly integrate ports for air admission, Revealed by the descending piston (or an air piston in engines featuring dual pistons per cylinder), the exhaust pathway can follow two routes. Closing the exhaust before the inlet during the compression stroke is vital for optimizing the charge. However in piston-controlled events, the engine's geometry may pose challenges. While feasible in engines with exhaust valves, in a single-piston engine, the closure of the inlet and exhaust mirrors their opening (Figure 2.11).

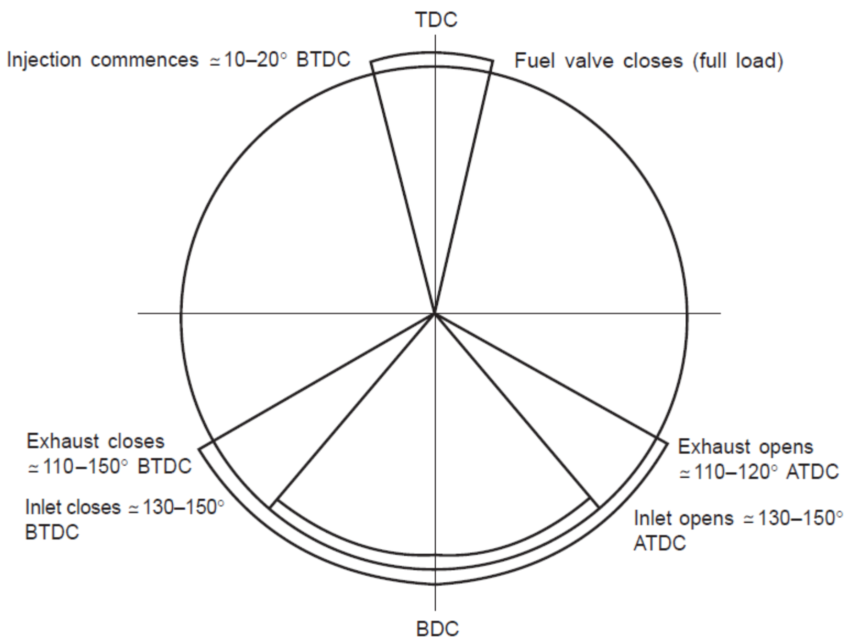

Figure 2.11 : The two-stroke operating cycle timing schematic [86].

Marine engine designers have recently grappled with the challenge of more stringent regulations on harmful exhaust gas emissions, imposed by regional, national, and international authorities in response to concerns about atmospheric pollution.

Emissions from marine diesel engines primarily consist of oxygen, nitrogen, carbon dioxide, and water vapor, with smaller quantities of carbon monoxide, sulfur and nitrogen oxides, partially reacted hydrocarbons, and particulate matter. Nitrogen oxides (NOx), particularly concerning due to their carcinogenic nature and contribution to smog and acid rain, are produced thermally during high combustion temperatures. Sulphur oxides (SOx), resulting from sulfur oxidation in the fuel, contribute to acid rain, affecting ecosystems and groundwater quality [86] [90].

2.5.2 Emission and control techniques

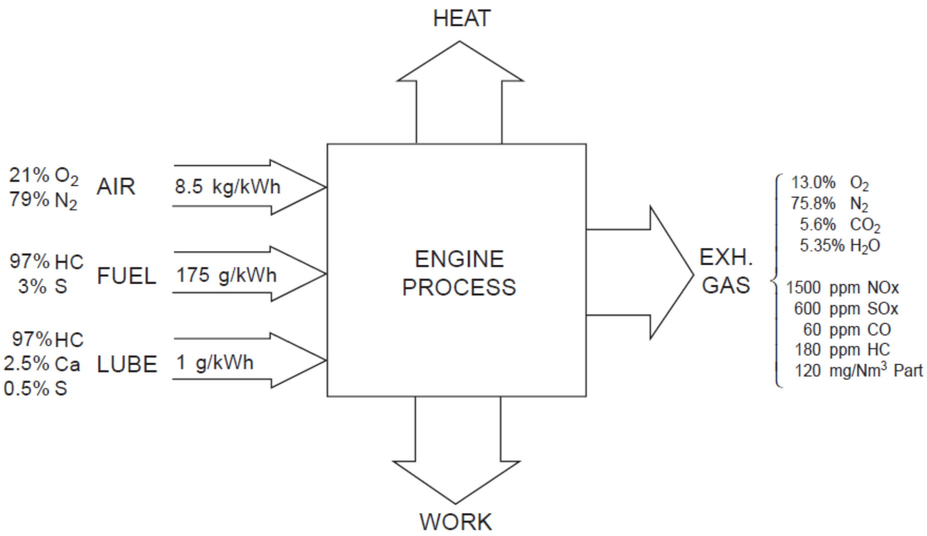

Figure 2.12 : Emission rates of a low-speed diesel engine [90][127].

Hydrocarbons, produced by incomplete combustion, and CO, a byproduct of leak combustion caused by a local air shortage, pose health and environmental risks. PM is a complex mixture arising from incomplete combustion, unburned lube oil, and other sources, constituting a small percentage of engine exhaust gases. Harmful emissions, accounting for about 0.25-0.4 percent by volume of the exhaust gas, depend on factors like fuel sulfur content and engine type as shown in Figure 2.12 [90].

Carbon dioxide (CO2) comprises about 6 percent of engine emissions and, although not toxic, contributes to the greenhouse effect. Diesel engines, with their higher thermal efficiency, result in lower CO2 emissions per unit of fuel burned compared to other heat engines. The international focus on the atmospheric impact of CO2 has led to measures to curb emissions, urging the marine industry to prepare for future legislation [90].

Improving the efficiency of modern diesel engines has limitations, prompting exploration of alternative strategies such as operating engines at fuel-saving points, using cleaner fuels, adopting diesel-electric propulsion, and considering diesel combined cycles. The maritime sector's high sulfur content in fuel significantly contributes to global sulfur oxide emissions. To address this, the International Maritime Organization (IMO) seeks a global cap on heavy fuel oil sulfur content and stricter sulfur limits in designated Sulphur Emissions Control Areas (SECAs).

Efforts to reduce sulfur emissions include burning low-sulfur fuels and imposing global and regional sulfur content caps. The implementation of selective catalytic reduction systems for lower NOx emissions also necessitates low-sulfur fuels to prevent catalyst fouling. The European Union advocates for stringent controls on air pollution, proposing a maximum sulfur content of 0.2 percent for fuels used in EU ports, potentially requiring uni-fuel ships to carry low-sulfur fuel specifically for port entry [90].

IMO initiated a global effort to control NOx emissions through Annex VI that corresponds to Marpol 73/78. Ships utilizing marine diesel oil and heavy fuel oil were identified as contributors to 7 percent of global NOx emissions, 4 percent of sulfur dioxide, and 2 percent of carbon dioxide emissions.

Annex VI comes into force 12 months after ratification by at least 15 states, constituting over 50 percent of the world's gross tonnage. Ships constructed after January 1, 2000, were required to comply, addressing engines with a power output exceeding 130 kW in new ships and existing ships undergoing major modifications as it represented in Figure 2.13 and Figure 2.14 [90].

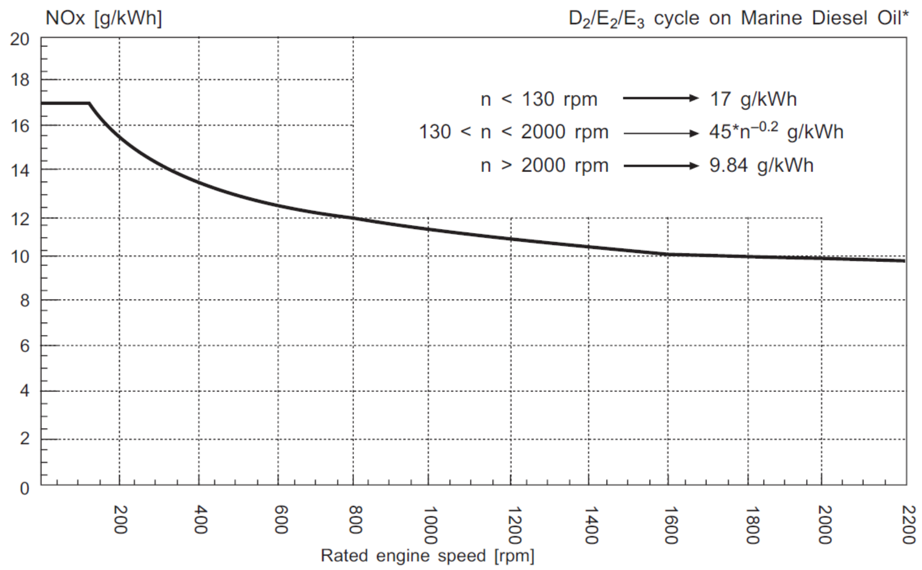

Figure 2.13 : NOx limits for marine diesel engine [90].

Compliance involves meeting NOx limits outlined by the IMO curve related to engine speed. Certification, according to the NOx technical code, and an EIAPP letter of compliance are required. IMO's current maximum allowable NOx emission levels vary based on engine speed categories, ranging from 17 g/kWh to 9.84 g/kWh.

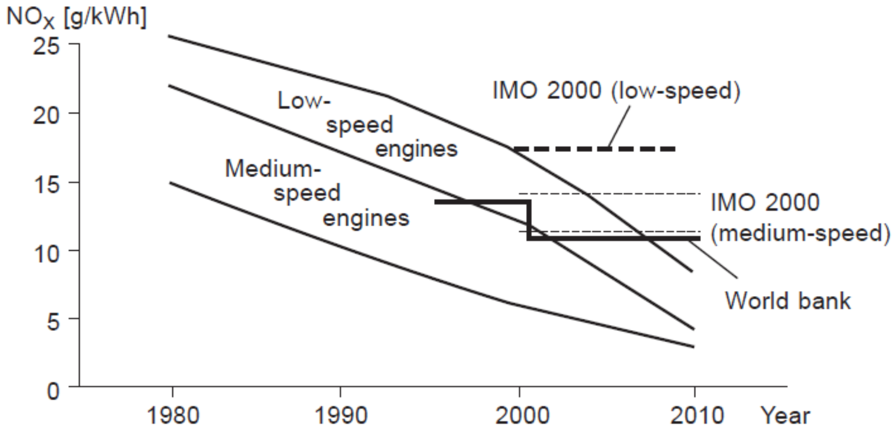

Figure 2.14 : NOx rates for 2 and 4 Stroke for marine diesel engine [90].

Regional authorities, like California's Air Resources Board, enforce stricter NOx and emissions controls. Sweden differentiates port and fairway dues, imposing higher fees on ships with higher NOx emissions. With ongoing IMO controls, reducing NOx emissions is prioritized by engine designers, balancing environmental concerns with fuel economy gains.

Factors influencing NOx formation include temperature and oxygen concentration. Two-stroke engines, particularly low-speed ones, tend to generate higher NOx emissions due to longer combustion times. To reduce NOx emissions, primary measures optimize combustion parameters, while secondary measures involve downstream cleaning techniques, achieving emission reductions of over 95 percent. NOx redcer techniques and the performance outputs are represented in Figure 2.15 and Figure 2.16.

Primary NOx reduction measures include water addition, altered fuel injection, combustion air treatment, and changes in the engine process. The goal is to lower maximum cylinder temperature, inherently reducing NOx emissions. Newer medium-speed engines address NOx emissions by employing longer strokes, higher compression ratios, and heightened firing pressures [86] [90].

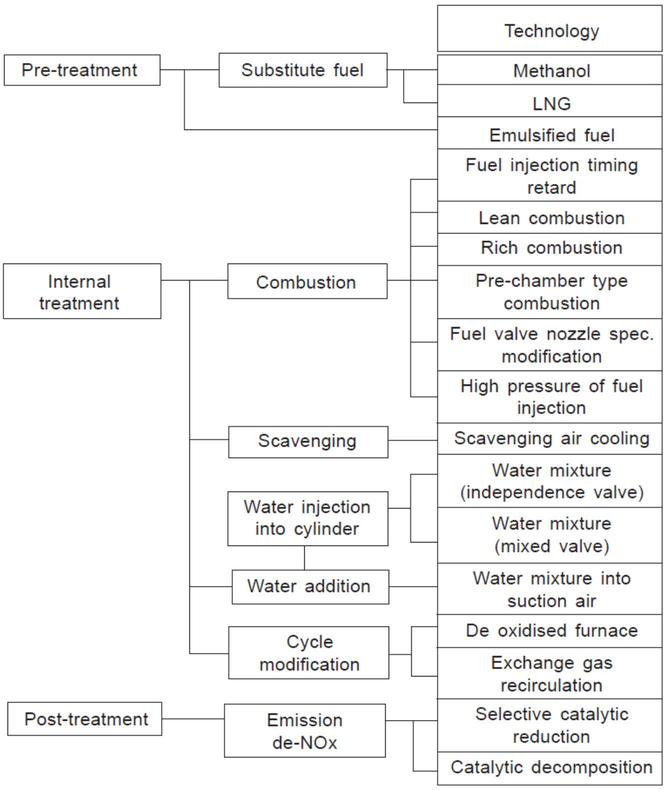

Figure 2.15 : NOx reducing techniques for diesel engines [90].

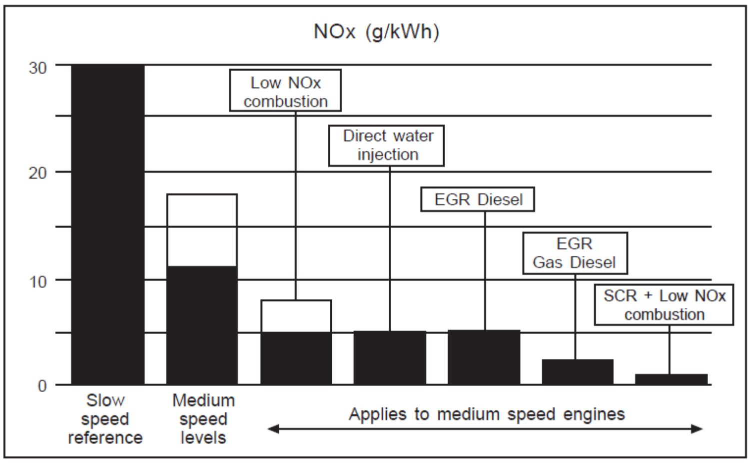

Figure 2.16 : NOx reducer performances [90].

Considering Exhaust Gas Recirculation (EGR) as another and most useful technique, EGR is a technique employed to modify the inlet air for the purpose of reducing NOx emissions, a methodology widely adopted in automotive applications. This process involves cooling and purifying a portion of the exhaust gas before reintroducing it to the scavenge air side. EGR influences NOx formation by reducing oxygen concentration introducing water and carbon dioxide from recirculated exhaust gas. The increased heat capacities of water and carbon dioxide play a role in lowering peak combustion temperature, effectively reducing NOx formation.

EGR proves to be an effective technique for reducing NOx emissions, achieving a notable 50–60% reduction without compromising the engine's power output. However, its practicality is often contingent on the type of fuel burned, with engines using cleaner fuels like low sulfur and low ash fuels, gas and alcohol, being more suitable. Engines operating on high sulfur fuel may face challenges related to the corrosion of crucial components such as turbochargers and intercoolers [90].

While primary methods generally suffice for complying with IMO NOx emission limits, more stringent regional controls may necessitate the adoption of secondary techniques, specifically exhaust gas treatment techniques, either independently or in conjunction with engine modifications. This discussion focuses on SCR systems, initially developed for land-based power stations and subsequently adapted for shipboard applications, demonstrating the capability to achieve NOx reductions exceeding 90% [90].

In the SCR process, exhaust gas is mixed with ammonia, rather in the form of a 40% urea solution in water, before traversing a specialized catalyst layer within a temperature range of 290 degC to 450 degC. The lower temperature limit is influenced by fuel sulfur content, as temperatures below 270 degC can lead to undesirable reactions between ammonia and SOx resulting in deposits. Excessive temperatures, on the other hand, may degrade the catalyst. NOx is effectively reduced to harmless gaseous by-products such as water and nitrogen, and a portion of soot and hydrocarbons undergoes oxidation within the SCR process reactor. Desirable catalyst qualities include low inertia to minimize ammonia slip, low pressure drop, short heating-up time, and resistance to fouling to ensure sustained performance over time.

The efficiency of catalytic conversion in SCR systems significantly relies on urea dosage. Higher dosages enhance conversion rates, but excessive urea can lead to ammonia slip downstream, adversely affecting the overall process and operational efficiency. Therefore, precise urea dosing, based on engine speed, load, and residual NOx levels, is crucial under various load conditions. Installation considerations include placing the SCR reactor before the turbocharger for low speed two-stroke engines depend on the temperature requirements, while post-turbocharger exhaust gas temperatures in four-stroke engines are sufficient for catalytic processes. In the presence of an exhaust gas boiler, it should be installed after the SCR, with ongoing catalyst development focusing on the temperature window [90].

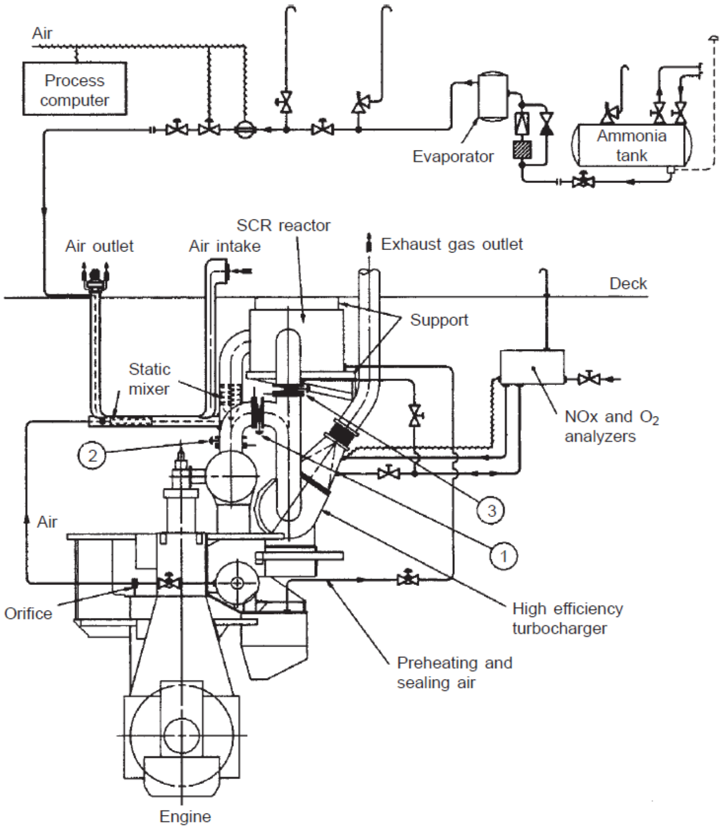

Figure 2.17 : Schematic view of low-speed diesel engine with SCR system [90].

SCR technology has demonstrated remarkable de-NOxing efficiency since the early 1990s in deep-sea and coastal vessels. Noteworthy NOx emission decrement, up to 95%, have been achieved by engendering marine SCR plants serving low-speed engines. These systems are strategically utilized, bypassing the SCR reactor on ocean legs to comply with IMO emission rules and activating it when entering regulated waters, thus achieving near-complete NOx control. Since its commissioning in 1992, SCR installations on marine engines, including those on fast car/passenger ferries, have become more prevalent, meeting the anticipation of stricter regulations and the quest for NOx emission levels of 2 g/kWh or lower. Compact solutions, reducing reactor space requirements, and integration into exhaust manifolds further facilitate applications in both newbuilding and retrofit projects [90]. Figure 2.17 represents schematic view of SCR.

2.6 Parameter Selection

The accurate modeling of non-linear systems, particularly in the intricate domain of internal combustion engines, hinges on the meticulous selection and collection of pertinent data. Engines, with their dynamic and multifaceted nature, exhibit non-linear behaviors influenced by a myriad of factors. From combustion dynamics to fluid dynamics, and from thermodynamics to mechanical interactions, the intricate interplay of variables demands a comprehensive dataset for meaningful modeling. The task of selecting input and output parameters becomes pivotal in this context, as it not only determines the depth of understanding but profoundly influences the efficacy of the model. The essence of successful engine modeling lies in the judicious choice of parameters, encompassing those that directly impact performance metrics and emission characteristics. As such, the practitioner must navigate through the plethora of potential variables, recognizing their interconnectedness, and meticulously curate a dataset that encapsulates the nuanced dynamics of the engine under diverse operating conditions. This initial step sets the foundation for robust and insightful modeling, ensuring that the resulting representations align with the intricacies of real-world engine behavior .

As evidenced by the comprehensive examination of prior literature in the field, the parameters identified as pivotal for modeling diesel engine performance and emissions exhibit noteworthy consistency across diverse research endeavors. Researchers and practitioners alike, in their pursuit of understanding and optimizing diesel engine behavior, consistently underscore the significance of specific input and output parameters. The synthesis of findings from various studies reveals a consensus on the crucial role played by parameters such as boost temperature and pressure, position of accelerator, coolant temperature, engine speed, load, engine torque, rail pressure, turbocharger speed and VGT position, EGR position and temperature, and exhaust gas pressure, and some others in shaping both performance and emission characteristics. This collective acknowledgment not only substantiates the reliability and relevance of these parameters but also forms the foundation for the present study's focus on these key contributors. Acknowledging the alignment of research findings in this manner reinforces the established importance of these parameters and guides the subsequent exploration into their nuanced effects on diesel engine dynamics.

Boost pressure, often regulated by the turbocharger, significantly influences diesel engine performance. Increased boost pressure enhances air intake, promoting better combustion efficiency. This results in higher engine power and torque, contributing to improved overall performance. However, excessively high boost pressures may lead to elevated temperatures and pressures in the combustion chamber, potentially causing increased NOx emissions. Striking the right balance in boost pressure optimization is crucial for achieving a harmonious blend of power, efficiency, and emission control. Boost temperature, closely linked to boost pressure, plays a pivotal role in shaping engine performance and emissions. Elevated boost temperatures contribute to higher combustion temperatures, fostering improved efficiency and power output. Nevertheless, excessive temperatures can lead to increased thermal stress and NOx formation. Precision control of boost temperature is essential for achieving optimal combustion conditions, ensuring both enhanced performance and reduced emissions.

The accelerator pedal position serves as a direct input from the driver and profoundly influences engine behavior. As the pedal position increases, more fuel is injected into the cylinders, resulting in higher engine speed, torque, and power. Careful modulation of accelerator pedal position is essential for achieving desired performance characteristics while managing emissions. Rapid and abrupt changes in pedal position can lead to transient conditions that may impact emission levels, emphasizing the need for sophisticated control strategies. Load, representing the demand on the engine, is a key parameter governing performance and emissions. Higher loads necessitate increased fuel injection and combustion rates to meet power requirements. While elevated loads can enhance engine efficiency, they may concurrently raise NOx emissions due to heightened combustion temperatures. Balancing load demands is crucial for optimizing both power delivery and emission control in diesel engines.

Coolant temperature influences the thermal conditions within the engine, impacting combustion efficiency and emissions. Optimal coolant temperatures facilitate efficient combustion and minimize emission levels. Below the recommended temperature range, incomplete combustion may occur, leading to elevated particulate matter and hydrocarbon emissions. On the other hand, excessively high coolant temperatures may contribute to NOx formation. Precise control of coolant temperature is essential for achieving a harmonious trade-off between performance and emissions.

Engine speed, measured in rpm, is a fundamental parameter dictating the frequency of combustion cycles. Higher engine speeds generally result in increased power output but may lead to higher NOx emissions. Controlling engine speed is critical for balancing power requirements with emission constraints, especially during transient conditions and varying operational loads. Engine torque, a measure of rotational force, directly influences power generation. Higher torque values contribute to enhanced power delivery and overall engine performance. However, torque levels must be managed within optimal ranges to prevent excessive thermal loads and NOx emissions. Strategic control of engine torque is essential for achieving desired performance characteristics while adhering to stringent emission standards. Rail pressure, indicative of fuel injection pressure in the common rail system, profoundly affects combustion characteristics. Elevated rail pressures contribute to finer fuel atomization and improved combustion efficiency, positively impacting performance. However, excessively high rail pressures may lead to increased NOx emissions. Precise control of rail pressure is essential for achieving a balance between combustion efficiency, power output, and emission control.

The Variable Geometry Turbocharger (VGT) position governs the geometry of the turbocharger vanes, regulating boost pressure. Optimal positioning enhances combustion efficiency, contributing to improved performance. However, improper VGT positioning may lead to compromised combustion conditions and increased emissions. Precise control of VGT position is pivotal for achieving an optimal balance between power delivery and emission control. Turbocharger speed is closely tied to boost pressure regulation. Higher turbocharger speeds contribute to increased air intake and enhanced engine performance. Nevertheless, excessive speeds may lead to increased mechanical stress and potential emissions concerns. Strategic control of turbocharger speed is vital for achieving an equilibrium between performance gains and emission control.

EGR position governs the amount of recirculated exhaust gases, impacting combustion temperatures and emissions. Increased EGR rates can mitigate NOx emissions by reducing combustion temperatures but may also influence power output. Precise control of EGR positioning is crucial for achieving the desired balance between emission control and performance. EGR temperature is a critical parameter in exhaust gas recirculation systems, influencing the temperature of recirculated gases. Elevated

EGR temperatures contribute to improved combustion efficiency and reduced NOx emissions. However, excessively high temperatures may lead to increased thermal stress and potential emission concerns. Strategic control of EGR temperature is essential for achieving optimal emission reduction without compromising engine performance. Exhaust gas pressure reflects the pressure within the exhaust system and is indicative of combustion efficiency. Proper exhaust gas pressure contributes to efficient pollutant removal through aftertreatment systems. However, excessively high pressures may lead to increased backpressure and potential performance concerns. Controlling exhaust gas pressure is crucial for optimizing both emission reduction and engine performance.

Turbocharger outlet temperature, employed to estimate fuel consumption, represents the temperature of air as it exits the turbocharger. This parameter is crucial for fuel efficiency calculations, as elevated outlet temperatures may indicate increased energy utilization in the combustion process. Precise monitoring and control of turbocharger outlet temperature contribute to accurate fuel consumption estimations and overall energy optimization. SCR outlet temperature is instrumental in the reduction of NOx emissions. Elevated SCR outlet temperatures enhance the efficiency of NOx reduction reactions. Careful control of SCR outlet temperature ensures optimal performance of the aftertreatment system, leading to effective NOx abatement without compromising other emission characteristics.

The preliminary objective of this study is to construct a comprehensive model for diesel engine performance and emissions, focusing particularly on key outputs, namely fuel consumption and NOx emissions. The utilization of collected input data is intricately designed for the individual prediction of these outputs, recognizing the presence of determinative inputs that significantly impact both fuel consumption and NOx emissions. The principal and shared inputs influencing fuel consumption and NOx emissions include boost temperature and pressure, position of accelerator, coolant temperature, engine speed, load, engine torque, rail pressure, turbocharger speed and VGT position,, EGR position and temperature, and exhaust gas pressure. Notably, the turbocharger outlet temperature is exclusively leveraged for estimating fuel consumption, while the SCR outlet temperature is instrumental for NOx estimation. The selection of these inputs, guided by an extensive literature search, serves as a foundational basis for assessing the intricate relationships within the model.

Emission legislations for both vehicle and marine engines are imperative in mitigating environmental impacts. Commonly known Euro standards for vehicle engines (Euro 5, 6, 7) and their heavy-duty counterparts align with the emission norms established by regulatory bodies. In the maritime sector, IMO standards, such as MARPOL Annex VI, set emission limits for marine diesel engines, driving the need for advanced technologies and modeling strategies to achieve compliance.

MARPOL, a key international convention addressing marine pollution, outlines strict criteria for emission control in maritime operations. To adhere to MARPOL standards, optimizing the modeling of marine diesel engines becomes paramount. Leveraging data-driven modeling, a cutting-edge approach, offers the potential to enhance accuracy and efficiency in predicting and controlling emissions. The optimization process involves refining engine parameters and control strategies to meet stringent environmental regulations without compromising performance.

In the contemporary industrial landscape, the significance of diesel engines is experiencing a resurgence, particularly within the realms of heavy-duty vehicles and marine applications. With the ongoing advancements in electric propulsion dominating the discourse in public road vehicles, the robust capabilities and efficiency of diesel engines have found an expanding niche in sectors demanding formidable power and reliability. The heavy-duty and marine industries, characterized by arduous operational requirements, increasingly rely on diesel engines to meet heightened performance expectations. Simultaneously, the stringent emission-related legislations, exemplified by the latest mandates from the IMO and the MARPOL, underscore the imperative for cleaner and more efficient diesel engine technologies. Against this backdrop, research endeavors dedicated to understanding and optimizing diesel engine performance and emissions have assumed a pivotal role. The convergence of escalating industry demands, evolving emission standards, and a dedicated focus on research initiatives collectively propels diesel engines into a pivotal position within the contemporary landscape of heavy-duty and marine propulsion systems.

3. MACHINE LEARNING METHODS

3.1 General Overview

The evolution of machine learning has witnessed a compelling journey, from its conceptual origins to its contemporary prominence as a transformative force in various fields. Originating from the intersection of computer science and statistics, machine learning represents a paradigm shift in computational approaches, empowering systems to learn from data and make informed decisions without explicit programming. As the intricacies of marine diesel engine modeling are explored, the historical trajectory of machine learning unveils its foundational principles and the strides it has made. Beyond its historical trajectory, understanding the diverse areas of application for machine learning becomes paramount. From predictive analytics to complex pattern recognition, machine learning techniques have found application in various sectors, each with its unique set of challenges and opportunities.

The roots of machine learning extend back to the mid-20th century when the groundwork for the concept was laid by pioneers such as Alan Turing and Arthur Samuel. The term "machine learning" itself was coined by Samuel in 1959, defining it as the ability of computers to learn without being explicitly programmed. Early developments, such as the perceptron algorithm and decision tree models, set the stage for more sophisticated techniques that emerged in subsequent decades. The 1980s saw the rise of neural networks, only to be followed by a period of reduced interest, often referred to as the "AI winter." However, the late 1990s and early 2000s marked a resurgence with the advent of support vector machines and ensemble methods. The 2010s witnessed an unprecedented surge in machine learning applications, propelled by advances in deep learning, reinforcement learning, and the availability of vast amounts of data. Machine learning has transcended its theoretical origins to become an integral component in diverse fields, influencing decision-making processes and augmenting human capabilities. In healthcare, disease diagnosis and prognosis are aided by machine learning, while finance leverages it for fraud detection and risk assessment models. The realm of natural language processing utilizes machine learning for sentiment analysis and language translation, enriching human-computer interactions. Beyond these sectors, significant relevance is found in the domain of system modeling and control, where machine learning offers a versatile toolkit for tackling complex, nonlinear systems. As the focus narrows to marine diesel engine modeling, the applicability of machine learning becomes evident in enhancing predictive accuracy and optimizing performance, with implications extending to emission reduction strategies and fuel efficiency improvements [99].

Comprehending the essence of machine learning necessitates delving into its technical and mathematical underpinnings. At its core, machine learning is rooted in statistical concepts and algorithms that enable systems to discern patterns and relationships within datasets. The foundational principles include supervised learning, where models are trained on labeled data, and unsupervised learning, which deals with unlabeled data to unveil inherent structures. Furthermore, the robustness of machine learning algorithms often hinges on optimization techniques, such as gradient descent, which iteratively refines models to minimize errors. Probability theory, linear algebra, and calculus emerge as pillars, offering the mathematical scaffolding upon which various machine learning models rest. [3ml] These models span a spectrum from traditional regression and classification algorithms to more intricate neural networks and ensemble methods, each catering to specific types of data and problem domains. As we venture into marine diesel engine modeling, a grasp of these technical foundations becomes pivotal in navigating the terrain where machine learning seamlessly integrates with the complexities of engineering systems. There are several advantages of machine learning methods compared to traditional theoretical modelling techniques:

Data-driven approach: Machine learning methods are inherently data-driven, meaning they can learn patterns and relationships from data without being explicitly programmed with the underlying physics or mathematics. This is particularly advantageous when dealing with complex, nonlinear systems, such as Marine Diesel Engines, where traditional modelling techniques may not be able to capture all the relevant interactions.

Flexibility and adaptability: Machine learning models can be easily adapted and modified to fit new data or address different problems. This allows for greater flexibility and scalability compared to traditional modelling techniques, which may require significant modifications to incorporate new data or handle different scenarios.

Improved accuracy: Machine learning models can often achieve higher accuracy than traditional theoretical models, especially when dealing with large or complex datasets. This is because machine learning models excel at capturing nuanced patterns and relationships within the data that may not be immediately obvious to a human modeller.

Reduced modelling time and costs: Machine learning models can often be trained much faster than traditional theoretical models, which can reduce the overall modelling time and costs. In addition, machine learning models can often be trained on existing data, eliminating the need for costly and time-consuming experimental or theoretical data collection.

Robustness to noise and uncertainties: Machine learning models can be trained to handle noisy or incomplete data, making them more robust to uncertainties and errors in the data. This is particularly advantageous in Marine Diesel Engine modelling, where data may be incomplete or subject to measurement errors.

Overall, machine learning methods offer numerous advantages over traditional theoretical modelling techniques, particularly in situations where the underlying physics or mathematics are complex or poorly understood, or where large amounts of data are available. However, it is essential to carefully evaluate the strengths and limitations of different machine learning techniques and to ensure that the models are properly validated and tested before deployment.

There are a variety of machine learning techniques, different versions of these techniques, and combinations with each other that can be used for Marine Diesel Engine modeling depending on the specific problem at hand and the data available. Mostly experimented common techniques that can be used are:

ANNs: The method is used to model complex, nonlinear relationships between input and output variables. They are well-suited for modeling Marine Diesel Engine systems, as they can take in a large number of input variables (such as temperature, pressure, fuel consumption, etc.) and produce accurate predictions of engine performance [99][100].

SVMs: SVMs are are robust machine learning algorithms employed for classification and regression purposes. SVMs operate by identifying the optimal hyperplane to effectively distinguish data into distinct classes or predict output values using input variables. SVMs can be useful for modeling marine diesel engine systems, especially when dealing with complex, high-dimensional data [99][100].

Decision Trees: DTs are simple, yet powerful machine learning models that can be used for both regression and classification and tasks. They work by recursively dividing the data into subsets based on the values of the input variables, and predicting the output based on the majority class or average value of the subsets. Decision trees can be useful for modeling Marine Diesel Engine systems, especially when dealing with small to medium-sized datasets [101].

Random Forests: RFs are a derivative of decision trees that combine the estimations of multiple decision trees to produce more accurate and robust predictions. Random forests can be useful for modeling marine diesel engine systems, especially when dealing with noisy or incomplete data.

Deep Learning: Deep learning techniques, such as CNNs and RNNs, can be used for marine diesel engine modelling when dealing with large, complex datasets that exhibit spatial or temporal dependencies. These techniques have shown promising results in areas such as fault detection and predictive maintenance [102].

Overall, the choice of machine learning technique will depend on the specific problem at hand, the available data, and the expertise of the modeler. It is important to carefully evaluate and compare different techniques before selecting the most appropriate one for a given Diesel Engine or Marine Diesel Engine modelling task. Therefore this study is designed to be a review in terms of examining and applying models that are frequently and successfully used in modeling diesel engines. In order to identify prominent models based on data type, number of data, and resolution of data, a comparison method similar to the examples in the literature and in a more comprehensive manner was followed.

3.2 Categorization of the Methods

Machine learning methodologies encompass a diverse landscape of techniques, each tailored to address specific challenges in data modeling. This categorization aims to provide a structured overview of these methodologies, beginning with overarching clusters and subsequently delving into more specialized subclusters.

A robust toolkit of machine learning methodologies is presented, providing varied approaches for modeling intricate relationships within data. In the domain of marine diesel engine modeling, where the complexities of nonlinear systems necessitate advanced analytical tools, a comprehensive understanding of the theoretical foundations of these methodologies is deemed essential. This section navigates through esteemed supervised learning techniques, each representing a distinct lens through which the multifaceted dynamics of engine performance can be deciphered. From the foundational principles of linear regression to the intricacies of neural networks, a unique perspective is contributed by each methodology. As this journey is undertaken, the twin objectives are to unveil the mathematical nuances governing these methodologies and to discern their applicability in the context of marine diesel engines [109].

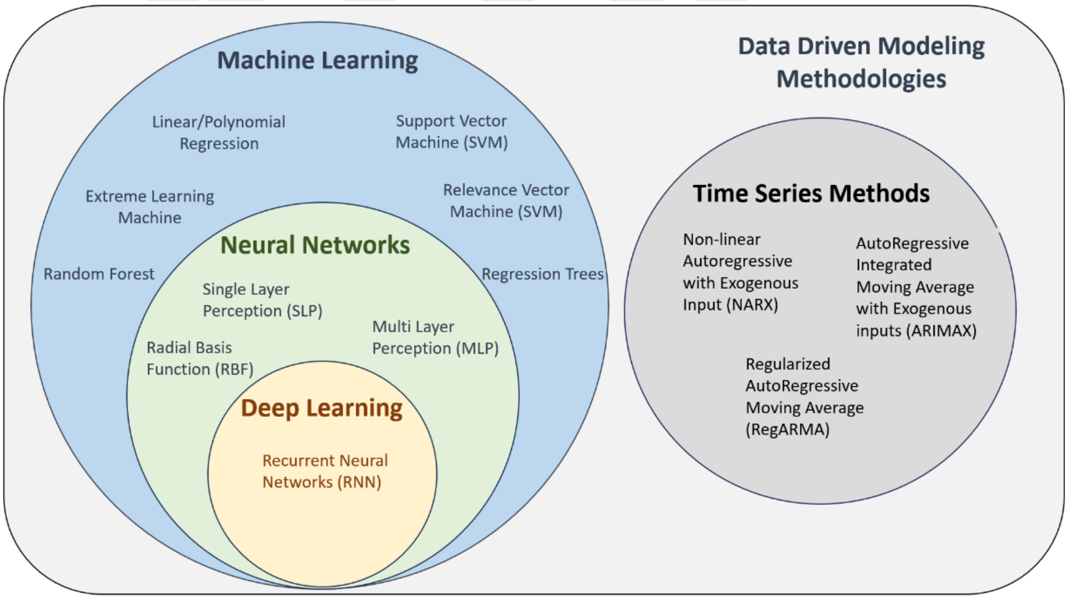

Figure 3.1 : Data driven modeling methodologies.

The distinction between traditional time series methodologies and contemporary machine learning approaches, though historically clear, is evolving into a more intricate relationship in current data analysis. Despite their historical separation, both methodologies share a central goal: discerning patterns and making predictions from data. In the context of modeling marine diesel engines, where variables interact dynamically and intricately, the imperative for robust estimation techniques becomes evident. This prompts an overarching perspective that transcends traditional boundaries, allowing us to perceive time series methods like NARX, ARIMAX, and RegARMA as integral elements within the broader domain of machine learning. Recognizing the common objectives of these methodologies not only bridges historical gaps but also fosters a more inclusive framework. This framework harnesses the strengths of both time series analysis and machine learning, providing a comprehensive approach to address the inherent complexities of engine performance modeling (Figure 3.1).

In the expansive landscape of machine learning methodologies, a foundational division emerges between supervised and unsupervised learning. Supervised learning, with its ability to utilize labeled data, proves particularly advantageous in the intricate realm of diesel engine modeling. The convenience of having a dataset with input-output pairs empowers these algorithms to discern patterns and make predictions effectively. Supervised learning further diverges into linear and non-linear categories, offering a nuanced perspective on modeling complexity. However, an alternative categorization unveils itself when considering the flow of information within the algorithms. Here, methodologies align into feedforward and feedback learning algorithms. Interestingly, within this framework, time series methodologies find a natural convergence with recurrent algorithms, illustrating the diverse ways in which machine learning strategies can be organized to tackle the complexities of engine performance modeling. This dual categorization not only reflects the varied nature of learning objectives but also highlights the adaptability of machine learning in addressing multifaceted challenges.

The categories encompassing some of the most widely used methods in the literature for diesel engine modeling, primarily falling under the supervised learning cluster are shown in Figure 3.2. Linear models, including Linear Regression and Polynomial Regression, offer simplicity and interpretability in capturing relationships within the data. The non-linear domain incorporates potent methodologies like SVM, random forests, and the intricate neural networks, especially within the realm of deep learning. Additionally, methods are classified based on their architecture, with feedforward models comprising linear and polynomial regression, SVMs, RFs, and ANNs, while recurrent architectures, notably recurrent neural networks (RNN), are situated within the neural networks category. This classification provides a comprehensive overview, capturing the diversity and adaptability of methodologies applied to the nuanced task of diesel engine modeling [99][100].

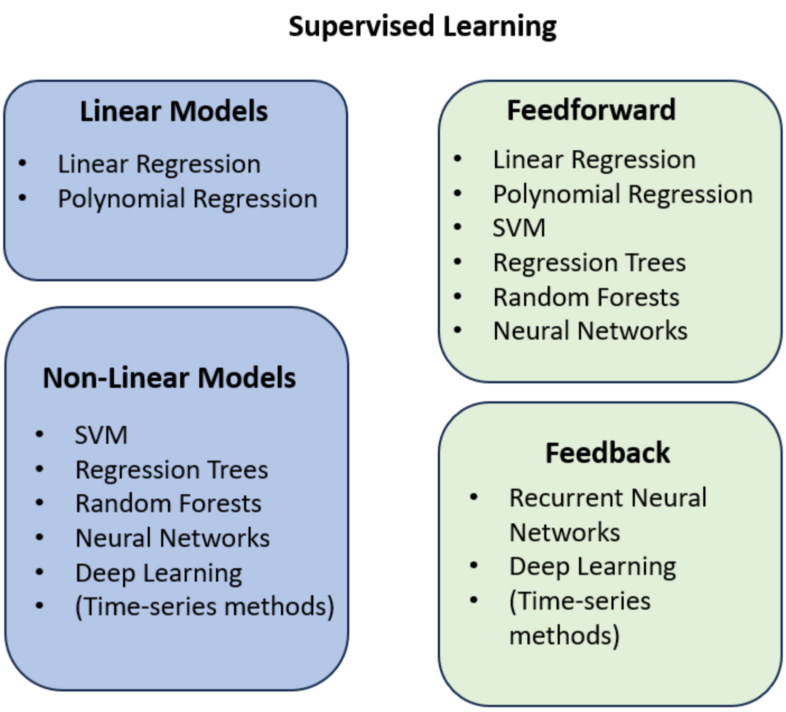

Figure 3.2 : Different category types of supervised learning algorithms.

Thus, within the scope of this study, the methodologies utilized in the literature for diesel engine modeling, as depicted in the figure, are expounded upon. Additionally, detailed explanations are provided in the literature concerning techniques that are comparatively less employed for diesel engine modeling but demonstrate a high estimation capability under specific conditions [109].

3.3 Regression

3.3.1 Linear regression

Linear Regression, a cornerstone of supervised learning, operates as a regression algorithm, primarily employed in forecasting. Its core purpose is to model the predictive value of a target variable based on independent variables, making it a vital tool for uncovering relationships between variables and making predictions [112].

At its essence, Linear Regression embodies a linear model, assuming a direct relationship between an input variable (x) and a single output variable ($y = h(x)$). This relationship (3.1) is expressed as a linear combination of input variables, where y is calculated as:

$$h(x) = wx + b \tag{3.1}$$

Here, w represents a vector known as weight, and b is a scalar referred to as bias. These parameters, weight, and bias, collectively define the model, and the aim is to estimate their values from a given dataset. In the case of Linear Regression, the hypothesis takes the form of a straight line. The fundamental task of Linear Regression is to learn a function or relation from a set of continuous data points. For instance, given a set of data points x and their corresponding y, the objective is to discern the relationship, termed the hypothesis. In Linear Regression, the hypothesis aligns with a straight line. Where w and b are the parameters of the model, to be determined from the dataset [113]. The estimation involves minimizing a cost function, denoted as 'j,' through the Mean Squared Error, calculated as the sum of squared differences between predicted and actual values (3.2).

$$j = \frac{1}{2m} \sum_{i=1}^{m} (h(x_i) - y_i)2 \tag{3.2}$$

Here, m denotes the number of data points. The process of optimizing the parameters to minimize the cost function 'j' involves employing gradient descent, a widely-used optimization algorithm in machine learning [113].

Linear Regression stands as a fundamental tool in predictive modeling, offering a balance of simplicity, interpretability, and predictive power. Its foremost strength lies in its simplicity; the model's straightforward linear relationship makes it accessible and easy to implement. Interpretability is a notable advantage, allowing practitioners to easily understand and communicate the impact of individual variables on the target outcome. However, these strengths coexist with certain limitations. Linear Regression postulates a linear relationship between variables, and its effectiveness diminishes when faced with complex, nonlinear data patterns. Assumptions of homoscedasticity and independence are inherent, and violations of these assumptions can effect the accuracy of predictions. Additionally, outliers can disproportionately influence the model, potentially leading to skewed results. While Linear Regression excels in capturing global trends within data, it might fall short in scenarios where intricate, non-linear relationships prevail. Nevertheless, recognizing these practical considerations enables practitioners to make informed decisions regarding the suitability of Linear Regression for a given modeling task.

The advantages and disadvantages of Linear regression can be defined clearly to establish the improved relationship with the further developed machine learning methods. The Advantages of Linear Regression in Diesel Engine Modeling are:

- Interpretability: Linear Regression provides a clear interpretation of the relationship between input variables and engine performance. This interpretability is crucial in the domain of diesel engine modeling, where understanding the influence of various parameters on performance is essential.
- Simplicity: The simplicity of the linear model aligns well with the basic understanding of the physical principles governing diesel engines. This simplicity not only aids in model development but also facilitates communication of results to stakeholders.
- Efficiency with Linear Trends: Linear Regression excels when the relationships within the data are approximately linear. In scenarios where diesel engine parameters exhibit linear trends, Linear Regression can provide accurate predictions with minimal complexity.
- Computational Efficiency: Linear Regression is computationally effective, making it proper for large datasets commonly encountered in diesel engine modeling. It allows for relatively quick training and prediction times [112].

The disadvantages of linear regression in diesel engine modeling:

- Assumption of Linearity: The core assumption of linear relationships might be limiting when dealing with the complex, nonlinear dynamics inherent in diesel engines. Engine performance is often influenced by nonlinear interactions between variables that linear models may struggle to capture accurately.
- Sensitivity to Outliers: Linear Regression is sensitive to outliers, and in diesel engine datasets, outliers may arise due to irregularities or sensor malfunctions. The impact of outliers on the model's coefficients can lead to biased predictions.
- Limited Capacity for Nonlinear Patterns: Diesel engine performance is characterized by intricate, nonlinear patterns. Linear Regression may inadequately represent such complexities, leading to suboptimal predictive

accuracy when compared to more complex models designed to capture nonlinear relationships.

- Assumption of Independence and Homoscedasticity: Linear Regression assumes independence and homoscedasticity of residuals, which might not hold in the case of correlated or heteroscedastic data often encountered in diesel engine modeling. Violation of these assumptions can affect the reliability of model predictions [112].

In summary, while Linear Regression offers simplicity and interpretability, its effectiveness in diesel engine modeling depends on the nature of the relationships within the data. For more accurate representation of the complex dynamics in diesel engines, consideration of more advanced modeling techniques may be necessary. Beneath the mathematical foundations of Linear Regression lies a methodology that, despite its simplicity, yields valuable insights into the dynamics of diesel engine performance. With its roots firmly grounded in a linear relationship between input variables and engine output, Linear Regression emerges as a powerful tool. Its efficacy is notably evident in its interpretability and computational efficiency, aligning seamlessly with the basic understanding of diesel engine principles. However, this simplicity comes with inherent limitations. Linear Regression assumes linearity and is sensitive to outliers, factors that may pose challenges when confronted with the intricate, nonlinear dynamics inherent in diesel engines. As we explore the advantages and disadvantages, it becomes clear that while Linear Regression offers transparency and efficiency, its application in diesel engine modeling requires careful consideration of the underlying data patterns [112].

3.3.2 Multiple linear regression

Expanding upon the principles of linear regression, Multiple Linear Regression emerges as a powerful extension capable of accommodating the complexities of marine diesel engine modeling. Unlike its predecessor, multiple linear regression considers multiple independent variables simultaneously, providing a comprehensive framework for capturing the interplay of various factors influencing engine performance [114].

Venturing beyond its foundational linear counterpart, Multiple Linear Regression (MLR) emerges as a sophisticated time series regression model with multivariate features tailored for the intricacies of marine diesel engine modeling. Acknowledging the temporal aspect of marine engine data, MLR encompasses an intercept value (c), each weighted by their respective coefficients ($\emptyset_i$). In the context of marine diesel engines, where time-varying parameters play a crucial role, MLR stands out as a versatile tool. The general equation (3.3) for MLR is expressed as:

$$y_t = c + X_1\emptyset_1 + \cdots + X_i\emptyset_i + \varepsilon_t \quad (3.3)$$

Here, yt represents the engine output at time t, $X_1, X_2, \ldots, X_i$ are the predictor time series, $\emptyset_1, \emptyset_2, \ldots, \emptyset_i$ are their respective coefficients, and ε_t is the error term accounting for unobserved factors. The parameter i denotes the number of predictors, emphasizing the model's capacity to handle multivariate inputs. This formulation aligns seamlessly with the dynamic nature of marine diesel engine data, where performance is shaped by a multitude of evolving factors. MLR's prowess in handling time series dynamics positions it as a cornerstone in marine engine modeling, allowing for nuanced insights into the temporal evolution of performance metrics. The interplay of various predictors, each with its distinct temporal trajectory, is encapsulated by MLR, offering a comprehensive understanding of how marine engines respond to changing conditions over time [114].

The usage of multiple linear regression in marine diesel engine modeling extends to scenarios where factors like fuel composition, load conditions, and environmental variables collectively impact engine efficiency. The advantages of multiple linear regression encompass not only its adaptability to multivariate settings but also its interpretability. By scrutinizing the coefficients, one can discern the magnitude and direction of each variable's impact on the engine's output. Furthermore, multiple linear regression facilitates the identification of significant predictors, aiding in the extraction of meaningful insights from the intricate web of marine engine dynamics [114].

3.3.3 Polynomial linear regression

Within the expansive domain of marine diesel engine modeling, Polynomial Regression emerges as an indispensable tool, seamlessly transitioning from the linear paradigm. While straightforward relationships are adeptly captured by linear models, the complex and often nonlinear interdependencies within marine engine data demand a more sophisticated approach. Introduced as an enlargement of linear models, polynomial regression provides for the accommodation of curved relationships between predictors and engine performance, driven by the inherent nonlinearities present in the marine engine domain. Mathematical formulations extend beyond linear equations (3.4), permitting the inclusion of polynomial terms:

$$h\,(x) = w_o + w_1 x + w_2 x^2 \ldots + w_d x^d \tag{3.4}$$

In this passive construction, $w_o, w_1, \ldots, w_d$ represent the coefficients, and d is the degree of the polynomial. This enables the model to flexibly capture intricate nonlinear patterns that might be overlooked by linear counterparts. In scenarios where the impact of certain parameters on marine diesel engine performance is not strictly linear but may vary with higher-order interactions, Polynomial Regression finds utility. For example, the relationship between fuel composition and engine efficiency might exhibit a quadratic or cubic nature. The advantages of Polynomial Regression in this context lie in its ability to adapt to the complex dynamics of marine engines, offering a more accurate representation of the true relationships at play. However, caution is warranted with higher-degree polynomials, as they may introduce the risk of overfitting, capturing noise rather than genuine patterns in the data. Striking the right balance between model complexity and accuracy becomes crucial, making Polynomial Regression a valuable yet nuanced tool in the marine diesel engine modeling toolkit [105].

3.4 Artificial Neural Networks (ANN)

In the exploration of non-linear modeling for marine diesel engines, ANNs emerge as a formidable tool capable of navigating intricate relationships and capturing nonlinear patterns. Inspired from the intricate organization of the human brain, ANNs are comprised of interconnected nodes organized into layers—input, hidden, and output. The dynamic interplay of weights and biases within the network allows intricate patterns and relationships within the data to be discerned, making ANNs well-suited for the multifaceted nature of marine engine dynamics. Unlike traditional linear models, the ability of ANNs to automatically learn and adapt to intricate patterns positions them as a sophisticated approach to capturing the diverse interactions between engine parameters. In the context of marine diesel engine modeling, ANNs can be tailored to predict performance metrics, such as fuel efficiency or emissions, by considering a multitude of input variables. The adaptability of ANNs to diverse and dynamic datasets is recognized, positioning them as a potent tool for uncovering hidden patterns in marine engine data. As their mathematical foundations, architecture, and applications in marine diesel engine modeling are explored, the versatility and potential of ANNs to enhance predictive accuracy become increasingly evident [99][100].

Neural networks represent a paradigm inspired by the intricate workings of the human brain. Technically, they are a computational model comprised of interconnected nodes known as neurons or units. Each connection between nodes carries a weight, representing the strength of the connection. The network processes information in a way that allows it to learn complex patterns and relationships within data. [115].

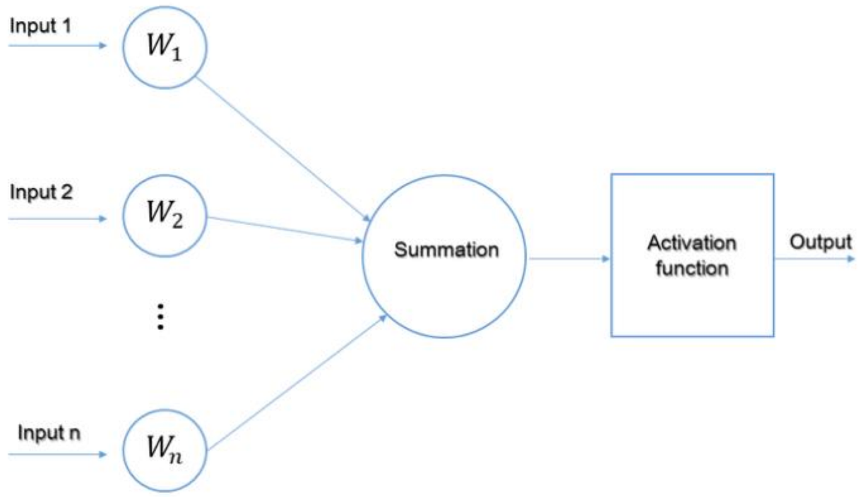

Figure 3.3 : Elementary structure of single layer neural network [115].

The neural network is comprised of interconnected nodes, each emulating the functionality of neurons. These nodes are integral to various elements that define the neural network's operation as represented in Figure 3.3.

- Input: The input layer serves as the entry point for external data, such as images or numerical vectors, without undergoing any immediate processing. For instance, it can include a collection of atmospheric measurements for a meteorological prediction model.

- Weight: Weights play a crucial role in assigning importance to features during the learning process. Scalar multiplication between input values and the weight matrix enhances the impact of certain features while diminishing that of others. For instance, in a music genre classification model, a high pitch note's influence may be magnified compared to average pitch notes.

- Activation Function: To introduce non-linearity and consider changing linearity with inputs, activation functions are employed. They prevent the output from being a simple linear combination of input values, enabling the network to accommodate non-linearities. Most used activation functions include unit step, piecewise linear, sigmoid, and Gaussian functions as shown in Figure 3.4 [115].

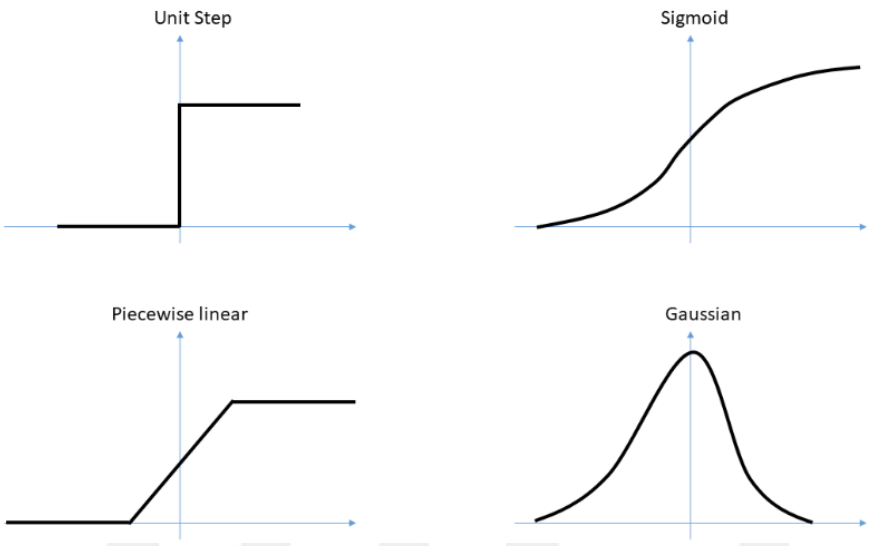

Figure 3.4 : Common activation functions [115].

- Bias: The bias alters the value generated by the activation function, functioning akin to a constant in a linear function. Essentially, it shifts the output of the activation function.

- Layers: The neural network consists of multiple stacked layers, each containing several neurons aligned in a row. Three types of layers are distinguished: Input, hidden, and output layers.

- Input Layer: The layer takes external data without immediate processing, transmitting information from the outside to the network.

- Hidden Layers: These layers, integral to deep learning, conduct calculations and extract data features. In tasks like image processing, early hidden layers detect borders and shapes, while later layers undertake more complex tasks like object classification.

- Output Layer: The last and final estimation is made by the that layer, leveraging data from preceding hidden layers. It's the layer from which the ultimate result is obtained, making it crucial. In classification and regression models, the output layer typically has a single node, although this can vary based on the nature of the problem [115].

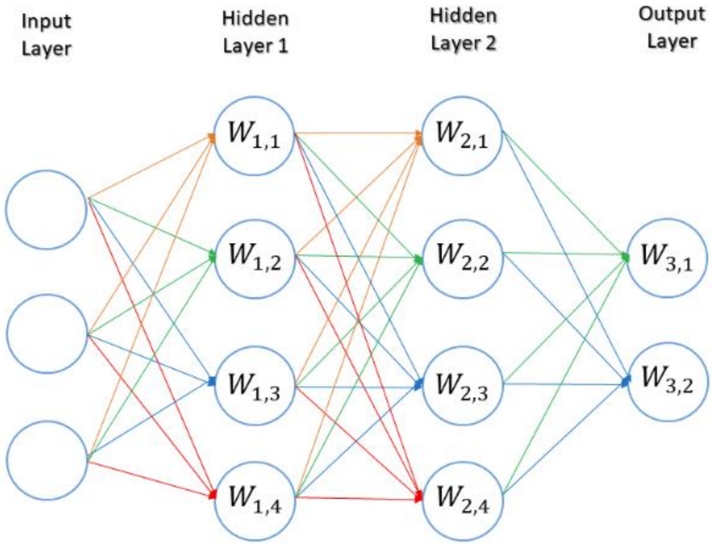

Figure 3.5 : Basic neural network structure [115].

The input nodes receive data expressed numerically, with each node assigned a numerical value corresponding to its activation level as shown in Figure 3.5. Higher numbers indicate greater activation. The network propagates this information outward, transmitting activation values from node to node based on connection weights, representing inhibition or excitation. Each node accumulates received activation values, adjusting its value according to its activation function. The activation traverses the network's hidden layers before reaching the output nodes. The output nodes then meaningfully convey the input to the external world. To address any disparity between the projected and actual values, the error is retroactively propagated by distributing each node's weights in proportion to its responsibility for the error [115].

Neural networks display diverse architectures and functionalities, resulting in various types categorized by their structures and applications. These types basically include feedforward neural networks (FNNs) that the information is moved in one direction, and feedback neural networks (FBNNs) also known as recurrent neural networks (RNNs), that include cycles in their structure, allowing them to retain information over time and making them suitable for sequential data [99][101].

Feedforward networks serve as the fundamental structures in neural networks. In these networks, information flows unidirectionally—from input to output—without forming cycles. This non-recurrent architecture includes processing units in each layer that receive inputs and perform computations based on weighted totals. The output from each layer becomes the input for the subsequent layer [115].

Considering the structure of neural networks, a feedforward network comprises interconnected layers—inputs, hidden layers, and outputs. Each layer contains processing units, and information flows unidirectionally through the layers. The single-layer perceptron (SLP), a basic type, has a single layer of output nodes, and learning is often facilitated by back-propagation. The multi-layer perceptron (MLP), on the other hand, incorporates multiple hidden layers, enabling the network to handle intricate patterns. The perceptron, a foundational component of feedforward networks, processes multiple binary inputs, assigns weights to them, and produces a binary output. In mathematical terms, the perceptron's output is determined by the sum of weighted inputs and a threshold function [99][101].

3.4.1 Single layer perceptrons (SLP)

SLP comprises a single layer of output nodes as shown in Figure 3.6 and is limited to linear separations, making it suitable for simple tasks. The output is determined based on the sum of weights (3.5):

$$y = f(w_1x_1 + w_2x_2 + \cdots + w_nx_n) \quad (3.5)$$

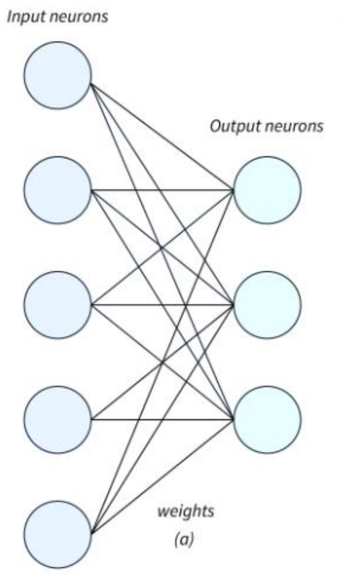

Figure 3.6 : Single layer perceptron neural network structure [116].

3.4.2 Multi layer perceptrons (MLP)

The multi-layer perceptron employs multiple layers of nodes, allowing it to handle complex patterns as represented in Figure 3.7. In mathematical terms, the output of an MLP with L layers. So the output y is determined as (3.6):

$$y = f(\ W_L \,.\, f\big(W_{L-1} \ldots f(W_l . X)\big)) \tag{3.6}$$

where W_i represents the weight matrix for layer i, f is the activation function, and X is the input [116].

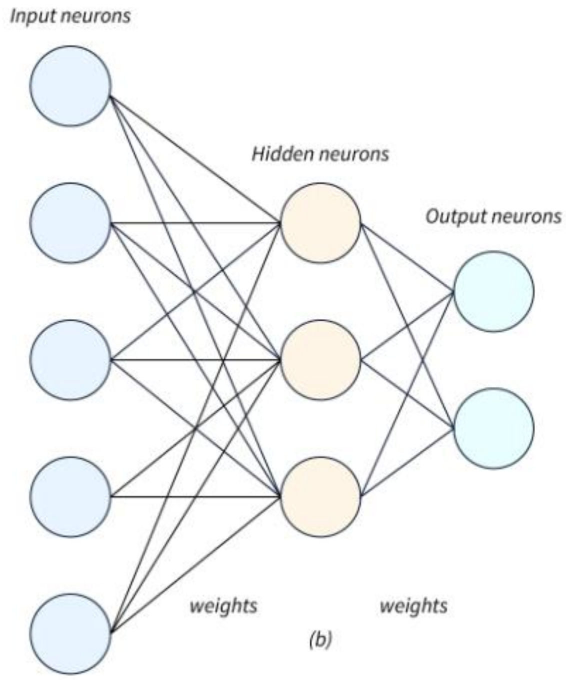

Figure 3.7 : MLP architecture [116].

The training of a feedforward neural network is a critical phase involving the adjustment of weights between neurons based on a dataset. This iterative process aims to enhance the model's predictive accuracy by minimizing errors.

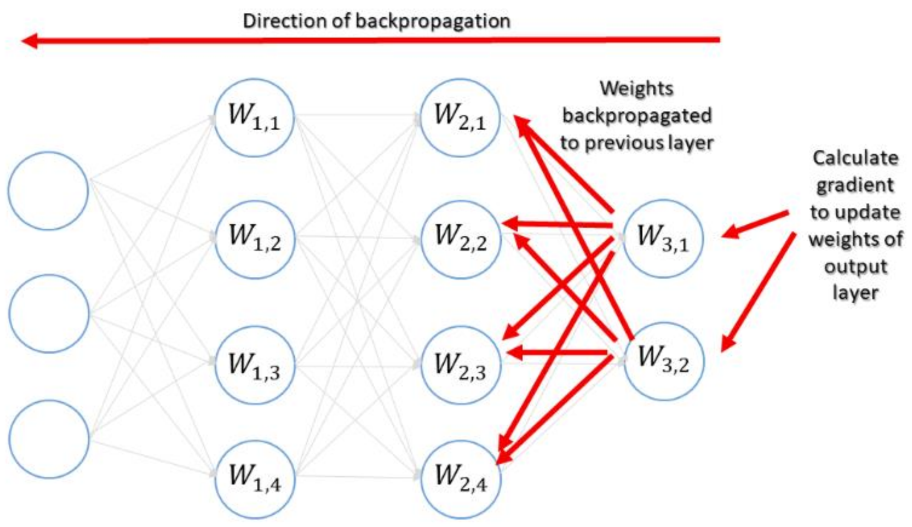

Figure 3.8 : Back propagation for a neural network [115].

In the feedforward phase, input data traverses the network, undergoing weighted summation and activation functions at hidden layers, ultimately reaching the output layer for prediction. Subsequently, in the backpropagation phase, the prediction error is computed and propagated backward through the network. The weights are then adjusted to reduce this error, a process vital for refining the network's performance.

The primary algorithm for training a feedforward network is back-propagation. Schematic view is of back-propagation represented in Figure 3.8. This technique adjusts the network's weights based on the error rate observed in the previous iterations. The back-propagation algorithm efficiently computes the gradient of the loss function for a single weight, layer by layer, utilizing the chain rule. While it calculates the gradient, it doesn't specify how to apply it, extending the computational scope of the delta rule. In the backpropagation algorithm, the weights are updated using the gradient descent method. The weight update Δw for a weight w is given by (3.7):

$$\Delta w = -\eta \frac{\partial J}{\partial w} \tag{3.7}$$

where η is the learning rate, and J is the cost function.

Training involves an iterative application of gradient descent optimization. This process continually passes the dataset through the network, updating weights to minimize prediction errors. The goal is to refine the model's performance through multiple passes, ensuring it reaches a success level of accuracy on the training data.

The training of feedforward neural networks is inherently an iterative learning process. As the dataset cycles through the network, weights are adjusted, and the model refines its understanding of complex patterns within the data. This iterative refinement, driven by gradient descent, continues until the network achieves a desired level of proficiency. In summary, the training of feedforward neural networks is a dynamic process involving forward and backward phases, facilitated by the backpropagation algorithm. This iterative learning, guided by gradient descent optimization, is fundamental for shaping the network's ability to make accurate predictions. The intricacies of weight adjustments and error minimization collectively contribute to the network's enhanced performance over successive iterations [115].

Backpropagation is a widely utilized training algorithm in the literature, particularly prominent in the domain of diesel engine modeling where precision in predictions holds paramount importance. Researchers frequently employ backpropagation to train neural networks, aligning with the specific requirements of diesel engine performance modeling [99][101].

The versatility of backpropagation extends across different neural network architectures, including both SLPs and MLPs. It serves as a pivotal algorithm for adjusting weights in these architectures, contributing significantly to their enhanced performance. Both SLPs and MLPs find common ground in their utilization of the backpropagation algorithm for training. This shared methodology involves adjusting weights to refine predictive accuracy. The coexistence of SLPs and MLPs with backpropagation underlines its effectiveness in enhancing the capabilities of diverse neural network structures. To visually illustrate the structural intricacies, supportive figures are included, elucidating the architecture of Feedforward Neural Networks, Perceptrons, and the Backpropagation Algorithm. These visuals provide a comprehensive overview of how information flows through the network and the pivotal role played by backpropagation in the training process.

While backpropagation stands as a prevalent method, alternative training approaches like GAs and PSO have garnered attention in literature, specifically in the context of training SLPs and MLPs for diesel engine modeling. These methods seek optimal weight configurations to enhance model performance, offering complementary strategies to the widely used backpropagation. Genetic algorithms draw inspiration from the principles of natural selection and genetics. These algorithms operate on a population of potential solutions, applying genetic operators like mutation and crossover to evolve towards optimal solutions. In the context of SLP and MLP training for diesel engine modeling, GAs aim to discover optimal weight configurations by mimicking the evolutionary processes observed in biological systems. PSO is inspired by the collective behavior of bird flocks or fish schools. It involves a population of particles that navigate through the solution space, tuning positions based on their own experience and the experiences of their neighbors. In training SLPs and MLPs for diesel engine modeling, PSO seeks optimal weight configurations by enabling particles to converge toward promising regions in the solution space, fostering collaborative exploration and exploitation of the search space. These alternative methods contribute diverse optimization strategies, offering complementary approaches to traditional backpropagation for achieving optimal performance in neural network training.

Beyond the realm of Feedforward Neural Networks, diesel engine modeling incorporates RBFNs and SVMs as noteworthy methodologies. RBFNs leverage radial basis functions as activation functions, contributing to their effectiveness, while SVMs excel in handling high-dimensional data through the strategic application of kernel functions. The inclusion of these methodologies enriches the landscape of approaches employed in diesel engine modeling, catering to diverse modeling requirements [100].

3.4.3 Radial basis function (RBFNN)

RBFNNs represent a prevalent form of artificial neural networks specifically designed for function approximation challenges. Distinguished by their global approximation capability and rapid learning speed, RBF networks stand out among neural network variations. They fall under the category of feedforward networks and are trained using a supervised training algorithm. An intriguing feature of RBFNNs is their streamlined architecture, comprising just one hidden layer utilizing the radial basis function as the activation function, renowned for its potent approximation capabilities.

The RBFNN's computational process involves calculating the weighted sum of inputs through Gaussian transfer functions in the hidden layer. This layer contains RBF neurons, each equipped with a prototype vector, comparing input vectors to assess similarity. The RBF neurons output values inversely proportional to the distance from their center, exhibiting a bell curve response [117].

In an RBFNN, the output of each neuron in the hidden layer is computed using a radial basis function. The typical structure involves three layers: input layer, hidden layer with radial basis functions, and an output layer. The output y_k of the k-th neuron in the hidden layer is calculated as (3.8):

$$y_k = \emptyset\left(\frac{||x - c_k||}{\sigma_k}\right) \tag{3.8}$$

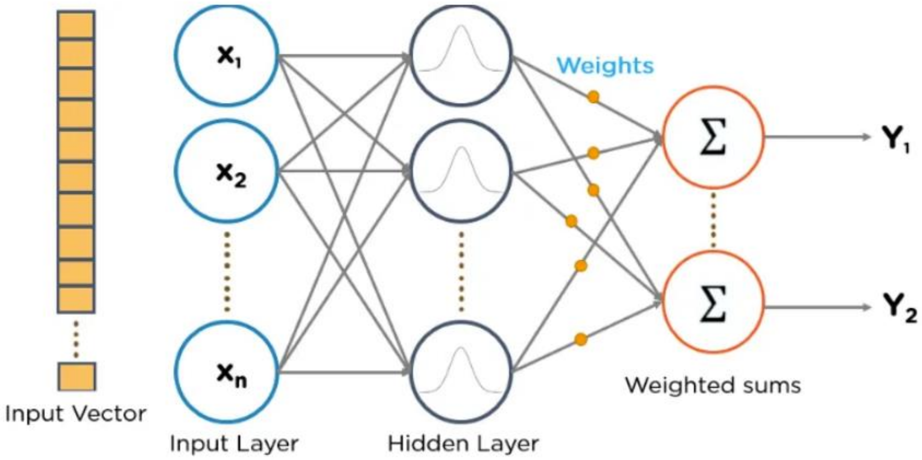

Figure 3.9 : Radial basis function neural network [117].

where x is the input vector, c_k is the center of the k-th neuron, σ_k is the width parameter, and $\emptyset$ is the radial basis function. RBFNNs classify inputs based on their similarity to examples from the training set. The input vector traverses the input layer and interacts with RBF neurons as shown in Figure 3.9. These neurons employ Gaussian transfer functions, producing outputs proportional to input similarity. The output layer, through a weighted sum of RBF neuron activations, categorizes the input, showcasing the network's distinctive scoring mechanism [117].

RBFNNs are extensively employed in diesel engine modeling due to their proficiency in capturing intricate non-linear relationships. With applications in function approximation problems, RBFNNs, with their unique architecture, prove effective in scenarios where a single hidden layer can achieve powerful approximation. RBFNNs boast several advantages, notably their effectiveness in function approximation, attributed to the potent radial basis functions employed in their single hidden layer. This streamlined architecture contributes to computational efficiency during training, making RBFNNs particularly useful in capturing intricate non-linear relationships. However, challenges arise in determining optimal parameters, such as the number of

RBF neurons, which can impact the network's performance. Additionally, the complexity introduced by the radial basis function might limit the interpretability of the model. Despite these limitations, RBFNNs remain a popular choice in diesel engine modeling and other applications requiring robust function approximation capabilities [106][107].

3.5 Support Vector Machines (SVMs)

SVM is a strong ML algorithm employed for solving intricate classification, regression, and outlier detection challenges. In diesel engine modeling and various other domains such as healthcare, natural language processing, signal processing, and image recognition, SVMs have proven effective in tackling complex problems. While initially designed for binary classification, SVMs can be adapted to handle computationally intensive multiclass problems. This adaptation involves constructing multiple binary classifiers that collectively form SVMs capable of multiclass classifications [99].

In mathematical terms, SVMs utilize kernel methods to transform data features through kernel functions. These functions facilitate the mapping of complex datasets into higher dimensions, making the separation of data points more straightforward. This process, known as the "kernel trick," efficiently and inexpensively achieves data transformation into higher dimensions. The training process involves optimizing w and b to maximize the margin while ensuring that data points are correctly classified. For non-linearly separable data, SVM uses the kernel trick to map the input space into a higher-dimensional space, making it possible to find a hyperplane [99] [100] [118].

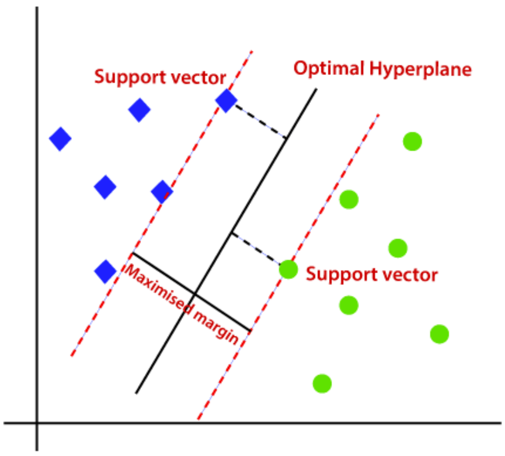

Figure 3.10 : Support vector machine structure.

In the realm of diesel engine modeling, the SVM algorithm aims to identify a hyperplane that distinctly segregates data points that included different classes. The hyperplane is strategically positioned to maximize the margin, representing the largest distance between data points. This margin optimization ensures robust classification. The dimensions of the hyperplane are determined by the features present in the dataset, translating to a straight line in two-feature scenarios or a two-dimensional plane in cases with three features (Figure 3.10).

The exploration of specialized variants addressing unique challenges is deemed essential. A least squares approach to SVM is introduced by least square SVM presenting advantages such as simplified solutions to linear equations and reduced dependence on hyperparameters. On the other hand, the handling of intricate, non-linear data is extended by Kernel or non-linear SVM. This non-linear classifier excels in situations where data cannot be distinctly separated by a straight line in a 2D space. The intricacies of Linear SVM and Kernel SVM will now be delved into, unraveling their mathematical foundations and application nuances.

3.5.1 Linear support vector machines (Linear SVM)

Linear SVM is focused on data classification with a clear linear separation. The identification of a hyperplane that distinctly segregates classes while maximizing the margin between them is pursued by the algorithm. This hyperplane is characterized by its linearity, rendering it suitable for scenarios where data points are separable by a straight line in the feature space. In the mathematical context, the objective of Linear SVM is to find a hyperplane defined by a set of linear equations. For a two-feature scenario, the hyperplane is a straight line, and for higher dimensions, it takes the form of a plane [118].

3.5.2 Kernel/Non-Linear support vector machine (Kernel SVM)

Kernel SVM steps in when faced with non-linear data that defies classification by a simple straight line. Instead of relying on 2D space, the introduction of additional dimensions through kernel functions is facilitated by Kernel SVM, allowing the creation of hyperplanes that adeptly separate classes even in non-linear scenarios. In the mathematical formulation, kernel methods are employed by Kernel SVM to efficiently map data into higher dimensions. The kernel trick is pivotal, as it enables the algorithm to handle non-linear data without explicitly calculating the transformations. The resulting hyperplane is a culmination of the mapped features, facilitating the classification of non-linear data [118].

3.6 Relevance Vector Machines (RVMs)

RVM stands as an alternative to SVM and is rooted in the principles of sparse Bayesian inference. Remarkably akin to SVM in formulation, RVM introduces distinctive advantages, steering clear of the necessity for additional hyperparameters. An invaluable feature of RVM is its provision of probabilistic predictions, contributing to an intricate understanding of uncertainty in the prediction process. Furthermore, RVM exhibits a propensity for delivering highly sparse solutions, contributing to enhanced interpretability and computational efficiency. RVM, rooted in sparse Bayesian inference and sharing a parallel formulation with SVM, distinguishes itself by eliminating the requirement for extra hyperparameters. It offers probabilistic predictions, ensuring a nuanced understanding of prediction uncertainty, and excels in delivering sparse solutions. Despite RVM's training time scaling cubically with sample numbers, an accelerated learning algorithm has been devised to enhance efficiency. The accelerated algorithm, coupled with RVM's probabilistic nature, positions it as a preferable choice in various applications, including the present study [119].

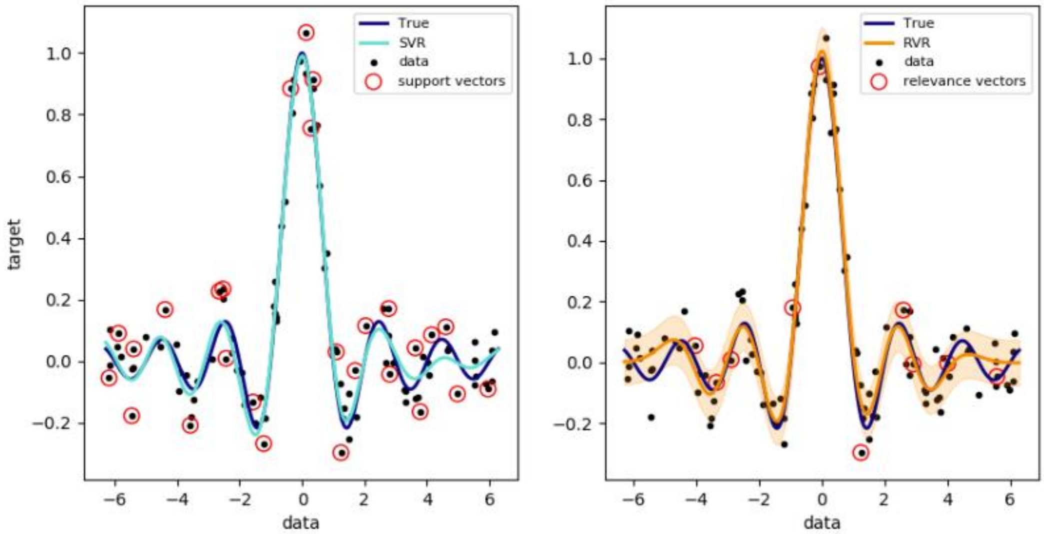

Figure 3.11 : Comparison between SVM and RVM [120].

RVM's mathematical foundation aligns closely with SVM but with certain nuanced differentiations. A notable departure lies in the avoidance of additional hyperparameters, streamlining the modeling process. The core methodology involves sparse Bayesian inference, leveraging the Bayesian framework to induce sparsity in the model. This not only aids in efficient model training but also facilitates a probabilistic interpretation of predictions. RVM's formulation aims at maximizing the marginal likelihood, a pivotal criterion in Bayesian statistics. The accelerated learning algorithm associated with RVM operates in cubic time concerning sample numbers, a limitation ameliorated by a specialized algorithm. This accelerated learning algorithm initializes with an empty model and iteratively incorporates or excludes samples within the similar principal framework, optimizing the marginal likelihood and adjusting weights simultaneously. This unique amalgamation of Bayesian principles, sparsity induction, and an accelerated learning approach renders RVM an attractive choice, particularly considering its favorable computational properties [121] (Figure 3.11).

3.7 Extreme Learning Machines (ELMs)

ELMs have emerged as a novel learning paradigm designed for single-hidden-layer feedforward neural networks (SLFNs), addressing the challenge of slow learning in traditional algorithms. This methodology extends to generalized SLFNs, where the hidden layer structure is not restricted to neuron-like entities. ELM's fundamental concept revolves around a single hidden layer, and notably, the parameters of this layer, encompassing input weights and biases, are not subject to meticulous tuning. Instead, these parameters are assigned randomly, introducing an element of independence from the training data. Subsequently, the determination of output weights, linking the hidden layer to the output layer, is achieved analytically through a Moore–Penrose generalized inverse. This analytical calculation contributes to remarkably fast training times, facilitated by concise computational steps. Moreover, the analytical determination of output weights effectively overcomes challenges like local minima and issues related to improper learning rates encountered in traditional ANNs. In essence, ELMs represent a paradigm characterized by simplicity and efficiency, presenting a distinctive approach to training in the domain of neural networks [108].

In ELM, the network's input-to-hidden layer weights and biases are randomly assigned and remain fixed. The hidden layer output is then computed using an activation function, often a sigmoid or radial basis function. The output layer weights are determined through a simple linear regression on the training data. This unique structure eliminates the need for iterative tuning of weights, contributing to faster training times. Hidden layer output can be represented as (3.9):

$$H = \sigma(W_{in} . X + B_{in}) \tag{3.9}$$

Where H is the hidden layer output, σ is the activation function, W_{in} is the input-to-hidden layer weight matrix, X is the input data B_{in} is the bias for the hidden layer. The output layer weights W_{out} are then determined through linear regression (3.10):

$$Y = H. W_{out} \tag{3.10}$$

Extreme Learning Machines (ELMs) diverge significantly from Support Vector Machines (SVMs) in their training approach and regularization techniques. While SVMs necessitate the resolution of a quadratic programming problem, ELMs embrace a distinctive one-pass learning strategy. In ELMs, the hidden layer weights are assigned random values and remain fixed, with the output layer weights computed in a singular pass. This streamlined approach stands in contrast to the iterative nature of SVMs. Moreover, in the realm of regularization, SVMs often demand meticulous fine-tuning of hyperparameters. In contrast, ELMs leverage the randomization inherent in the assignment of hidden layer weights, serving as a built-in mechanism for implicit regularization. This randomized approach diminishes the reliance on extensive hyperparameter tuning, contributing to the efficiency and simplicity that characterize ELMs. Extreme Learning Machines offer a fast and effective alternative to traditional learning algorithms. The incorporation of kernel functions in ELMs enhances their capability to handle non-linear patterns, providing flexibility in various applications [108].

3.8 Decision Trees

Decision Trees are versatile machine learning models that operate by recursively partitioning the dataset based on feature values. At each node of the tree, a decision is made regarding the feature that best splits the data, optimizing a criterion such as Gini impurity or information gain. In the context of diesel engine modeling, Decision Trees can be employed for tasks such as fault diagnosis and performance prediction. DTs stand as a non-parametric technique in supervised learning, serving purposes in both classification and regression. The objective is to construct a predictive model for a target variable, utilizing straightforward decision rules derived from the dataset's features. Conceptually, a tree functions as a representation of a piecewise constant approximation.

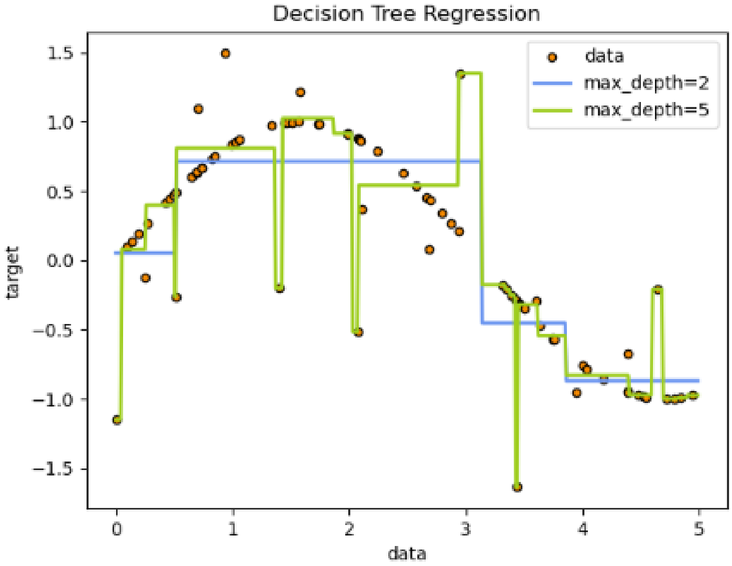

Figure 3.12 : Decision tree regression example [122].

Decision trees offer several advantages that contribute to their widespread use as represented in Figure 3.12. Firstly, they are straightforward to understand and interpret, allowing stakeholders to gain insights easily. The minimal data preparation required is another notable advantage. Decision trees work well with raw data, eliminating the need for complex preprocessing steps, and some algorithms even handle missing values. The logarithmic cost for prediction makes them computationally efficient. Additionally, decision trees are versatile, capable of handling both numerical and categorical data. Their multi-output capability further enhances their applicability. Decision trees represent white box models, providing an understandable logic for decision-making, unlike black box models. Models created by decision trees can be statistically validated, offering a measure of reliability.

Moreover, decision trees often perform robustly even when some assumptions about the underlying data model are not precisely met. However, decision trees come with certain drawbacks. Overfitting is a common issue, where the model gets more complicated and becomes not able to take into account the new data. Techniques like pruning are necessary to combat this problem. Stability can be a concern, as minor variations in input data may lead to vastly different trees. The predictions from decision trees are non-smooth, as they provide piecewise constant approximations.

Learning an optimal decision tree is a computationally challenging task, and heuristics are often used to approximate the solution. Decision trees may struggle to express certain complex concepts efficiently. Additionally, the creation of biased trees is a risk, especially when certain classes dominate in the dataset. Balancing the dataset before fitting is recommended to mitigate this bias. Despite these drawbacks, the advantages of decision trees make them a popular and widely used machine learning tool [101].

3.8.1 Regression trees

Regression Trees, a subtype of Decision Trees, are tailored for regression problems. Instead of predicting discrete classes, they estimate a continuous output. In the context of diesel engine modeling, Regression Trees can be utilized for predicting numerical values like engine efficiency or emissions based on input features.

Considreing mathematical background, regression trees are a form of decision tree specifically designed for predicting numerical outcomes. The mathematical background of regression trees involves the recursive partitioning of the feature space into distinct regions, assigning a constant value (typically the mean) to each region.

- Splitting Criteria: At each node of the tree, the dataset is split into subsets based on a chosen criterion, often minimizing the mean squared error. The algorithm explores different splits across features and thresholds to determine the optimal division.
- Recursive Partitioning: The recursive nature of the algorithm continues, creating a binary tree structure. This process involves selecting the best feature and threshold at each node to minimize the prediction error.
- Leaf Node Values: Once a certain stopping criterion is met, such as a predefined tree depth or a minimum number of samples in a node, the algorithm stops splitting, and the values assigned to the leaf nodes become the predictions for the corresponding regions.
- Prediction Process: For a given input, the algorithm traverses the tree, following the splits based on the input features until a leaf node is reached. The predicted value for the input is then the constant value assigned to that leaf node. The mathematical formulation involves defining the splitting criteria, determining the optimal feature and threshold for splitting, and establishing

rules for assigning constant values to the leaf nodes. Regression trees are effective for capturing complex non-linear relationships in the data, making them valuable for regression tasks where the target variable is continuous [101] [123].

3.8.2 Random forests

RFs are ensemble techniques for learning that builds multiple DTs and merges their estimations. Each tree is structured by a random set of the data and a random subset of features at each split. This randomness introduces diversity among the trees, mitigating overfitting and enhancing generalization. RFs are robust, and their ensemble nature often leads to improved predictive performance. In diesel engine modeling, RFs can offer accurate predictions and handle complex relationships within the data.

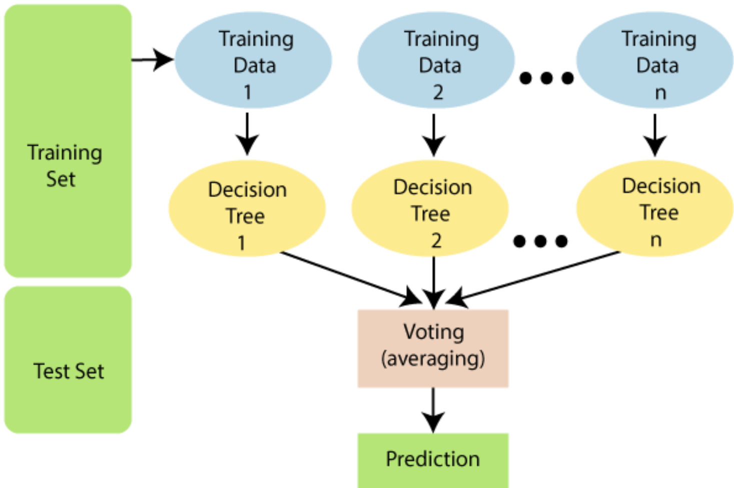

Figure 3.13 : Working of random forest algorithm [124].

Random Forest exhibits versatility by effectively executing both Classification and Regression tasks. It demonstrates proficiency in managing extensive datasets characterized by high dimensionality. Notably, this algorithm contributes to heightened model accuracy while concurrently addressing concerns related to overfitting. On the flip side, it is essential to acknowledge that, despite its applicability to both classification and regression tasks, Random Forest may demonstrate a relatively reduced suitability for regression-oriented assignments. This versatile algorithm is applicable to both classification and regression problems, employing ensemble learning principles. Rather than DT, RF incorporates multiple decision trees trained on diverse subsets of the dataset. The final output is determined through the averaging of predictions from each tree, relying on majority votes to enhance predictive accuracy (Figure 3.13).

The algorithm's efficiency is particularly noteworthy in handling both large datasets with high dimensionality and instances where a significant proportion of data is missing. The distinctive feature of RF is its compatibility to mitigate overfitting issues by incorporating a substantial number of trees in the ensemble, leading to higher accuracy. The algorithm's operational process involves two fundamental phases: the creation of the Random Forest and the prediction phase.

In the forest creation phase, Random Forest randomly selects K data points from the training set and builds decision trees associated with these chosen subsets. This process is repeated to create N decision trees in the ensemble. Subsequently, in the prediction phase, the algorithm aggregates predictions from each decision tree for new data points. The final assignment of new data points is determined by the category with the majority votes among the decision trees. For optimal performance of the Random Forest classifier, two key assumptions are considered. Firstly, the feature variable of the dataset should contain genuine values rather than guessed results, ensuring accurate predictions. Secondly, predictions from individual trees within the ensemble should exhibit low correlations, enhancing the overall predictive capacity of the Random Forest algorithm [124].

3.9 Deep Learning Algorithm

In conjunction with feedforward networks, feedback neural networks introduce a pivotal shift in architectural design by incorporating dynamic elements and feedback loops. This transition marks a departure from the unidirectional flow of information in feedforward networks to a more complex structure capable of retaining and utilizing information from previous states. One prominent example of feedback networks is the class of recurrent neural networks, characterized by cyclic connections within the network. This cyclical connectivity endows feedback networks with the ability to capture temporal dependencies and exhibit memory, rendering them particularly effective for tasks involving sequential data and context-awareness. Within the domain of diesel engine modeling, the integration of feedback neural networks stands as a crucial augmentation, enabling the capture of time-dependent dynamics and intricate interactions within the system.

Recurrent Neural Networks (RNNs) stand out among feedback neural networks for their inherent capacity to model sequential dependencies and contextual information. Unlike feedforward networks, RNNs encompass cyclic connections, allowing them to maintain an internal state that captures information from previous inputs. This cyclical structure makes RNNs well-suited for tasks involving time-series data, natural language processing, and any context-dependent information [99][102].

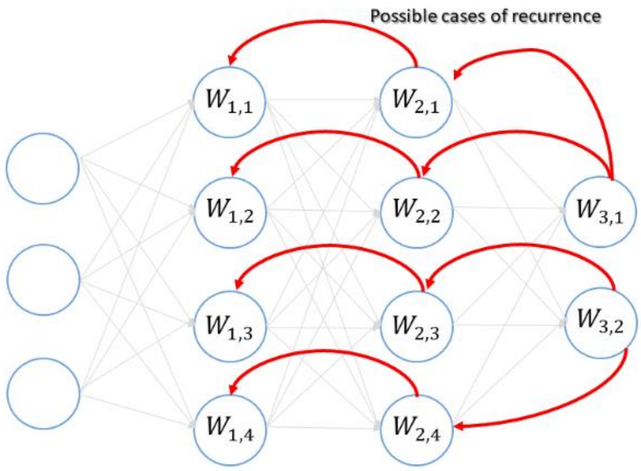

Figure 3.14 : Feedback neural network structure [115].

Mathematically, the essence of RNNs lies in their recurrent nature, represented by the propagation of information from one step of the network to the next as shown in Figure 3.14. Considering a simple RNN unit (3.11):

$$h_t = f_{RNN}(W_{hx} \cdot x_t + W_{hh} \cdot h_{t-1} + b_h) \qquad (3.11)$$

Here, W_{hx} and W_{hh} are weight matrices, b_h is the bias vector, and f_{RNN} corresponds to activation function. This recurrent formulation enables the network to maintain memory of past inputs and contribute to the output at the current time step.

In the context of diesel engine modeling, RNNs offer a distinct advantage when dealing with time-dependent variables and intricate relationships. The temporal aspect of RNNs makes them adept at capturing patterns and dynamics evolving over time, making them valuable tools for predictive modeling and system identification in the realm of diesel engine behavior.

Addition to recurrent neural networks (RNNs) and a generic feedback neural network structure a convergence in modeling perspectives is observed with nonlinear autoregressive methods. While feedback connections among neurons are leveraged by

RNNs to incorporate memory-like elements, temporal dependencies are captured by nonlinear autoregressive methods like NARX and NLARX, albeit through distinct mechanisms. This alignment in modeling objectives establishes the foundation for exploring synergies, as indicated by studies combining both techniques to enhance predictive capabilities. The shared commitment of both frameworks to unraveling the temporal intricacies inherent in time series data is underscored by the consideration of feedback connections.

The delineation between traditional time series methods and machine learning approaches, while historically distinct, is becoming increasingly nuanced in contemporary data analysis. Both methodologies converge on a fundamental objective: extracting patterns and making predictions from data. In the realm of marine diesel engine modeling, where the interplay of variables is intricate and dynamic, the need for robust estimation techniques is paramount. This necessitates a perspective that transcends conventional boundaries, allowing us to view time series methods, such as NARX, ARIMAX, and RegARMA, as integral components within the broader machine learning domain. The common aims shared by these methodologies are acknowledged, not only bridging historical gaps but also embracing a more inclusive framework that harnesses the strengths of both time series analysis and machine learning to tackle the complexities inherent in engine performance modeling. Therefore, in this study, within the scope of prediction base data driven technologies, nonlinear autoregressive modeling methods have been categorized as a machine learning methodology in a broad perspective, and data driven modeling comparisons have been made between these methods and standard machine learning methods that are used efficiently and frequently in the literature.

3.10 Time Series Methods

Time series methods serve as indispensable tools in the identification and modeling of complex dynamic systems, with applications ranging from finance to engineering. The distinctive feature of time series analysis lies in its ability to recognize patterns, trends, and dependencies within sequential data, thereby providing a robust foundation for making predictions. In the context of diesel engine modeling, where the interactions among various variables unfold dynamically over time, time series methods emerge as a crucial asset. Their intrinsic capability to capture temporal dependencies and evolving patterns aligns seamlessly with the intricacies of engine performance. These methods become particularly potent in extracting valuable insights from historical data, facilitating accurate predictions, and aiding in understanding the underlying mechanisms governing engine behavior. Among the notable time series methodologies employed for such modeling endeavors are NARX, ARIMAX, and RegARMA each offering unique advantages in unraveling the temporal complexities inherent in diesel engine systems.

3.10.1 NARX

The NARX model represents a class of nonlinear autoregressive models that take into account both the previous and old values of the time series. NARX mathematically represented as (3.12):

$$y(t) = f_{NARX}\big(y(t-1), y(t-2), \dots, y(t-n), u(t-1), u(t-2), \dots, u(t-m)\big) + \varepsilon(t) \tag{3.12}$$

Here, $y(t)$ is the estimated output at time t, u(t) represents exogenous inputs, f is a nonlinear function capturing the relationship, and is the $\varepsilon(t)$ error term.

NARX models capture complex temporal dependencies in time series data by incorporating feedback connections among neurons. They excel in handling nonlinear relationships and can accommodate exogenous inputs, making them versatile for diverse modeling tasks. The training of NARX models involves adjusting connection weights based on historical data [125].

3.10.2 ARIMAX

The ARIMAX methodology, derived from the Box-Jenkins method in ARIMA, constitutes a hybrid model amalgamating Autoregressive (AR) processes, Moving Average (MA) processes, and integration. Nevertheless, the application of the traditional ARIMA technique proves unsuitable for diesel engine modeling, primarily due to its reliance on univariate features. Given the inherent multivariate nature of the diesel engine model, the ARIMAX model has been devised to construct a more apt multivariate statistical model (3.13).

$$(1 - \emptyset_1 L - \cdots - \emptyset_P L^p)(1 - L)^D y_t = c + X_1\beta_1 + X_r\beta_r + (1 + \theta_1 L + \cdots + \theta_q L^q)\varepsilon_t \tag{3.13}$$

the representation of variables in the context of autoregressive order (p), degree of integration (D), number of predictors (r), and moving average order (q). Additionally, the constants c and ε_t denote the constant error. When the lag polynomial is simplified using lag operator notation, Equation (3.14) assumes the following form;

$$\emptyset(L)(1-L)^{D}y_{t}=c+\sum_{i=1}^{r}\beta_{i}X_{i}+\theta(L)\varepsilon_{t} \qquad (3.14)$$

$\emptyset(L)$ and $\theta(L)$ are lag operators.

ARIMAX models, rooted in the Box-Jenkins method, integrate auto regressive, integrated, and moving average elements. Unlike ARIMA, ARIMAX extends to multivariate settings, allowing the inclusion of exogenous variables. While powerful for univariate time series, ARIMAX is limited when facing multiple features, hindering its use in diesel engine modeling scenarios [126].

3.10.3 RegARMA

RegARMA is a modeling approach grounded in regression, incorporating auto regressive moving average time series errors. It aligns with the linear effects of input time series through the application of the multiple linear regression technique. In essence, RegARMA presents a synthesis of MLR and ARMA. Unlike ARMA, the computation of errors in RegARMA takes a distinct path from the linear model, driven by assumptions such as homoscedasticity (3.15).

$$y_{t}=c_{ARMA}+\sum_{i=1}^{r}\beta_{i}X_{i}+\mu_{t} \qquad (3.15)$$

c is intercept and μ_t are errors. Assuming as linear model, the error (3.16) is written as;

$$(1-\emptyset_{1}L-\cdots-\emptyset_{P}L^{p})\,\mu_{t}=(1+\theta_{1}L+\cdots+\theta_{q}L^{q})\varepsilon_{t} \qquad (3.16)$$

With the simplification, error (3.17) is stated as;

$$\emptyset(L)\mu_{t}=\theta(L)\varepsilon_{t} \qquad (3.17)$$

RegARMA combines multiple linear regression with ARMA time series errors, accommodating linear effects of input time series. It provides flexibility by separating error calculations from the linear model, adhering to assumptions like homoscedasticity. However, RegARMA may face challenges in capturing complex nonlinear relationships, which are a strength of NARX models [126]. As a summary, NARX, ARIMAX, and RegARMA each offer unique strengths and limitations. NARX stands out for capturing nonlinear dependencies and flexibility with exogenous inputs. ARIMAX, while powerful in univariate settings, faces limitations in handling multiple features. RegARMA, with its regression-based approach, excels in scenarios where linear effects play a significant role.

3.11 Data Processing and Model Development

The systematic processing of data is the linchpin in the creation of robust artificial neural network models, especially when confronted with intricate challenges like diesel engine modeling. Each step in this meticulous journey, from the initial collection of relevant data to the final validation of the model, holds paramount significance. The process is not merely a routine but a meticulous art aimed at refining and preparing the raw material data for effective model training.

In the realm of diesel engine modeling, where the interplay of numerous variables demands precision, the systematic application of data processing steps ensures the reliability and generalization capacity of artificial neural networks.

The steps, from cleansing data to defining model architecture, from initialization to validation, contribute harmoniously to the quest for accurate predictions. This systematic approach stands as a testament to the commitment to excellence in the realm of artificial neural network modeling for intricate systems [103].

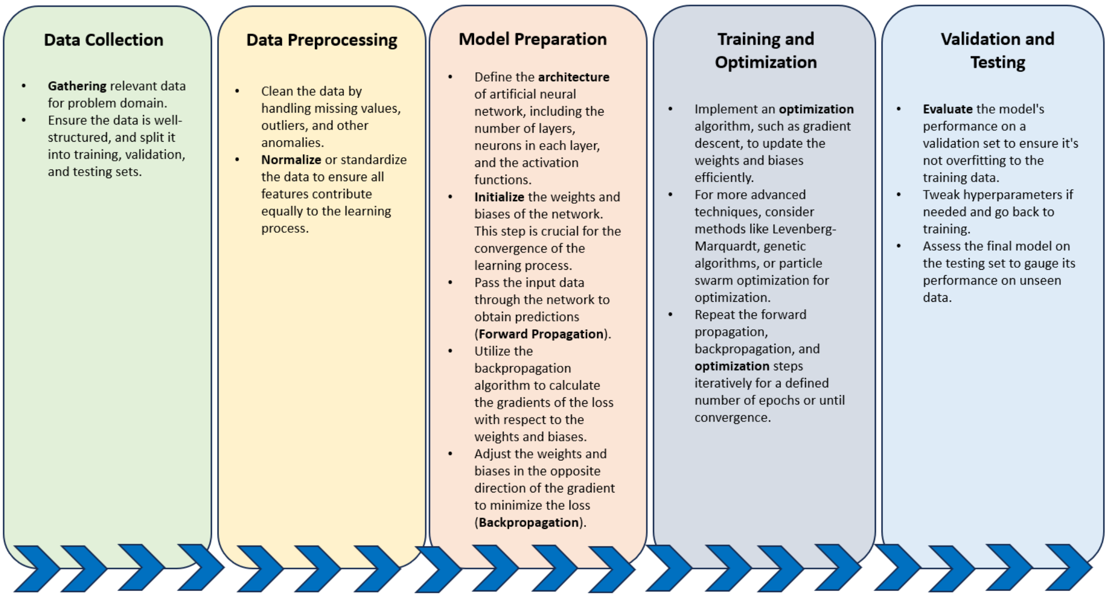

Figure 3.15 : Data processing for model development.

In the journey from collecting data to model validation, the process of data processing plays a pivotal role in ensuring the efficacy of artificial neural networks for complex problem-solving, such as diesel engine modeling. Commencing with data collection, the emphasis lies on gathering pertinent information for the problem at hand, structured meticulously into training, validation, and testing sets. Subsequent to data collection, the focus shifts to data preprocessing, involving the meticulous cleaning of data by addressing missing values, outliers, and anomalies. Furthermore, normalization or standardization procedures are implemented to harmonize features for an equitable contribution to the learning process. The subsequent steps delve into defining the network architecture, initializing weights and biases, executing forward propagation to derive predictions, and computing the loss to quantify the disparity between predicted and actual values. The indispensable backpropagation algorithm is then employed to compute gradients and fine-tune weights and biases. Optimization techniques, ranging from conventional gradient descent to more advanced methodologies like Levenberg-Marquardt or genetic algorithms, further refine the learning process. The iterative training process refines the model, with validation steps to guard against overfitting, and ultimately culminates in rigorous testing to assess the model's prowess in handling unseen data as represented in Figure 3.15. This comprehensive data processing pipeline stands as the bedrock of robust artificial neural network modeling for intricate systems like diesel engines [104].

ANNs play a pivotal role in machine learning, particularly in solving complex problems across various domains. The training and optimization processes are integral components of harnessing the predictive power of ANNs. The journey commences with the meticulous collection of pertinent data, which is subsequently subjected to rigorous preprocessing, including cleaning and normalization. Subsequently, the neural network architecture is defined, encompassing considerations such as activation functions, neuron and layer numbers employed.

To initiate the learning process, weights and biases of the models are meticulously initialized. Forward propagation follows, wherein the input data traverses the network to generate predictions, and the associated loss is computed as a measure of predictive accuracy. The crux of the learning occurs during backpropagation, an algorithm that computes gradients of the loss with respect to the network parameters. These gradients guide the adjustment of weights and biases, steering the model toward minimizing the loss function [104].

Optimization algorithms, like gradient descent, are then employed to efficiently update the network's parameters. For enhanced sophistication, alternative optimization methods like Levenberg-Marquardt, genetic algorithms, or particle swarm optimization can be considered.

Validation steps are interspersed throughout the training operation, allowing performance of model to be assessed on a separate dataset to guard against overfitting. Adjustments are made as necessary, often informed by insights derived from the validation phase. Finally, the trained model undergoes rigorous testing on a dedicated dataset, providing an objective evaluation of its ability to generalize to unseen data.

This structured approach encapsulates the systematic training and optimization of artificial neural networks, reflecting the synergy between data processing, network architecture, and iterative learning techniques, leading to models that exhibit robust predictive capabilities across diverse applications [103] [104].

3.11.1 Training and optimizations techniques

3.11.1.1 Training algorithms

Training algorithms are techniques used to adjust biases and weights of a model to zeroize the difference between predicted and actual outputs. The primary goal is to enable the model in terms of estimation accuracy for newly coming data (Figure 3.16).

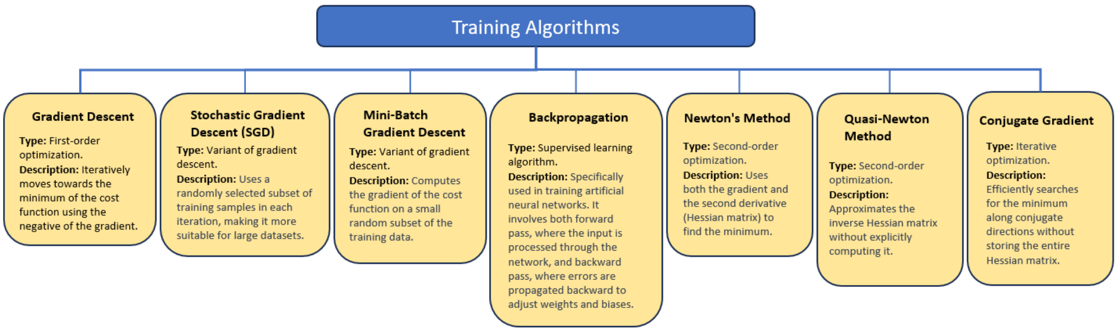

Figure 3.16 : Training algorithms.

Training algorithms play a pivotal role in the optimization of models, determining how the model learns from the provided data. Gradient Descent is a foundational first-order optimization technique that iteratively moves towards the minimum of the cost function, adjusting model parameters using the negative gradient. Stochastic Gradient Descent (SGD) introduces a variation, employing a randomly selected subset of training samples in each iteration, proving more efficient for large datasets. Mini-Batch Gradient Descent combines aspects of both, computing the gradient on a small, random subset of the training data. In the realm of neural networks, Backpropagation takes center stage. This supervised learning algorithm is specifically tailored for training artificial neural networks. It entails a forward pass, where input data traverses the network, and a backward pass, during which errors are meticulously propagated backward to fine-tune weights and biases.

Beyond basic gradient-based approaches, advanced optimization techniques include Newton's Method, a second-order optimization method that leverages both gradient and second derivative (Hessian matrix) information. Quasi-Newton Methods, exemplified by BFGS, offer a compromise by approximating the inverse Hessian matrix without explicit computation. Conjugate Gradient, on the other hand, adopts an iterative optimization strategy, efficiently navigating the search space along conjugate directions without the need to store the entire Hessian matrix. Each of these methods contributes distinct advantages to the training process, catering to specific challenges posed by diverse datasets and model architectures.

3.11.1.2 Optimization algorithms

Optimization techniques, on the other hand, refer to a broader set of methods used to find the best possible values for the parameters of a model. This includes not only adjusting the model during training but also fine-tuning other aspects of the learning process. Optimization techniques encompass a variety of algorithms beyond those used exclusively during the training phase. They include gradient-based methods like gradient descent, evolutionary algorithms like GA, swarm optimization like PSO, and other methods like simulated annealing. These techniques are employed to improve the efficiency, accuracy, and convergence of the learning process.

Optimization algorithms on the other hand are integral to refining machine learning models, influencing how efficiently models learn and adapt. Gradient Descent, a foundational technique, iteratively progresses towards minimizing the cost function by using the negative gradient. Stochastic Gradient Descent (SGD) introduces variability by employing random subsets of training samples, proving advantageous for large datasets. Mini-batch gradient descent strikes a balance by computing the gradient on small, random subsets.

In the realm of second-order optimization, Newton's Method incorporates both gradient and second derivative (Hessian matrix) information. Quasi-Newton Methods, exemplified by BFGS, approximate the inverse Hessian matrix without explicit computation. Conjugate Gradient, adopting an iterative strategy, navigates the search space efficiently by considering conjugate directions.

Evolutionary optimization techniques, such as GAs, emulate principles of natural selection to evolve potential solutions. PSO refers to normal behavior of organisms, with particles in the swarm exploring the solution space collaboratively. Simulated Annealing gradually reduces "temperature" to find the global minimum in a probabilistic optimization approach. Differential Evolution iteratively enhances candidate solutions for optimization as represented in Figure 3.17.

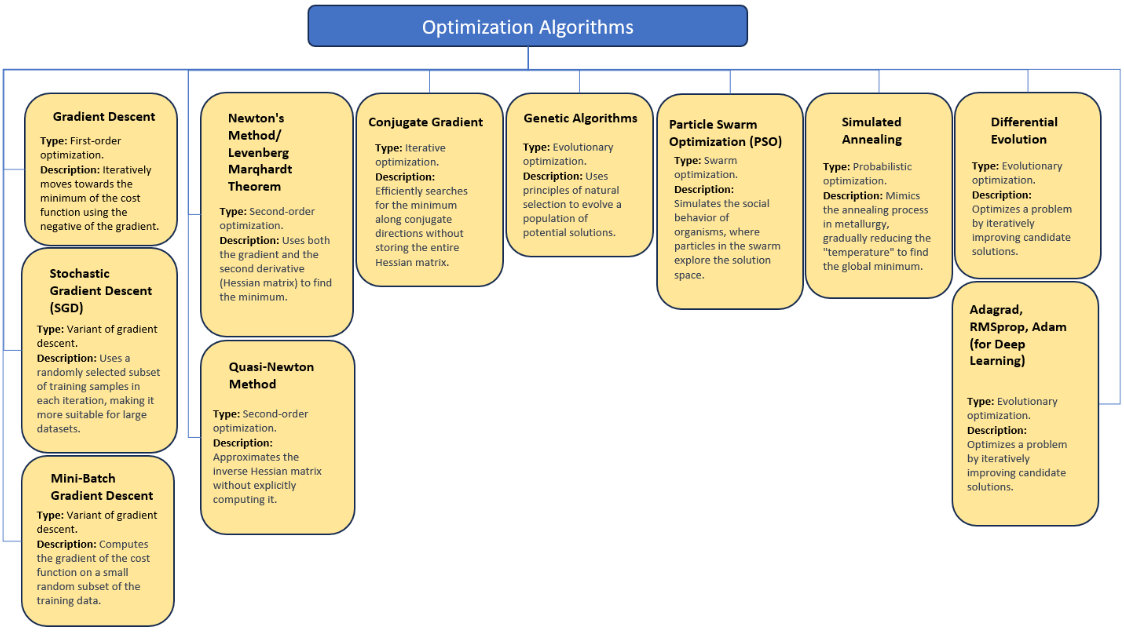

Figure 3.17 : Optimization algorithms.

For deep learning tasks, adaptive optimization techniques like Adagrad, RMSprop, and Adam dynamically adjust learning rates based on past gradients, enhancing convergence. The selection of these techniques hinges on various factors, including dataset size, available computational resources, and the nature of the objective function. Each algorithm caters to specific challenges and requirements posed by diverse optimization problems, contributing to the versatility of machine learning methodologies [102].

Levenberg-Marquardt

Levenberg Marquardt algorithm is one of the mostly used optimization technique widely employed to address nonlinear least-squares regression problems. Rooted in mathematical optimization, it finds its application in various domains, including neural network training. The primary objective of the Levenberg-Marquardt algorithm is to minimize the sum of the squared differencieses in nonlinear regression problems. This makes it particularly effective in scenarios where traditional methods might struggle to converge efficiently. The algorithm derives its name from Kenneth Levenberg and Donald Marquardt, both of whom independently proposed this optimization technique. The Levenberg-Marquardt algorithm can be seen as a hybrid approach, combining elements of both the steepest descent algorithm and the Gauss-Newton algorithm. This amalgamation allows it to strike a balance between the efficiency of gradient descent and the robustness of the Gauss-Newton methods.

In the context of neural network training, the Levenberg-Marquardt algorithm plays a crucial role in minimizing the error by judiciously adapting weights. Its key feature lies in its ability to handle nonlinear optimization problems efficiently, often converging faster than traditional methods. This efficiency is particularly advantageous in situations where the objective is to reach the optimal solution in a timely manner.

Mathematically, the Levenberg-Marquardt algorithm involves updating the weights in a way that minimizes the sum of the squared differences, thus adjusting the model parameters to fit the observed data optimally. This makes it a popular choice for problems where the relationships between variables are nonlinear and intricate. In the broader scheme of optimization algorithms, the Levenberg-Marquardt algorithm falls under the category of techniques specifically designed for addressing nonlinear optimization problems. Its versatility and effectiveness have led to its widespread use in various scientific and engineering applications, making it a valuable tool in the toolbox of optimization methods.

3.11.1.3 Normalization

After the meticulous process of data collection and the subsequent handling of missing values, outliers, and other anomalies in data preprocessing, normalization emerges as a pivotal step in the data processing pipeline. Following these initial stages, normalization takes place to ensure that the diverse features within the dataset share a standardized scale. This critical step is particularly beneficial for algorithms sensitive to variations in feature scales, such as k-NN or neural networks. By applying normalization techniques like Min-Max or Z-Score, the data becomes more amenable to modeling, preventing individual features from disproportionately influencing the learning process. The normalization process lays the foundation for a robust and stable input, contributing significantly to the overall effectiveness of machine learning models. Normalization is an crucial part in the data preprocessing pipeline, aiming to standardize the scale of features within a dataset. The primary objective is to ensure that no particular feature dominates the learning process due to differences in scale. This becomes especially significant for machine learning algorithms sensitive to variations in feature scales, such as k-NN (k-Nearest Neighbors) or neural networks [103].

3.11.1.4 Validation

In the journey from raw data to a well-performing machine learning model, a critical phase is the splitting of data into training, testing, and validation sets. The training set, typically comprising 70-80% of the data, serves as the foundation for the model's learning process. After training, the model's prowess is evaluated on the testing set, an independent subset representing real-world scenarios, allowing an assessment of its performance. To fine-tune the model without contaminating the testing set, a validation set, usually around 10-20%, is employed during training. This subset plays a pivotal role in adjusting hyperparameters and preventing overfitting.

Moving beyond simple percentage splits, more sophisticated techniques like cross-validation come into play. The aim of cross-validation is two-fold: first, to obtain a robust estimate of model performance, and second, to assist in critical decision-making processes during model development. Strategies like k-fold cross-validation, leave-one-out, and stratified cross-validation ensure a thorough evaluation even with limited data.

The validation set, used during training, is instrumental in preventing overfitting, a common pitfall where a model becomes too tailored to the training set's nuances. It acts as a safeguard, ensuring that the performance of model generalizes well to unseen data. Simultaneously, cross-validation steps in as a versatile tool. It aids in model selection by helping choose between different algorithms or hyperparameters and contributes to the final evaluation.

As this process unfolds, evaluation metrics such as RMSE, r-squared, BIC, and others find their place. These metrics serve as quantitative measures to assess how well the model aligns with the actual data. By incorporating validation and cross-validation practices into the machine learning pipeline and subsequently using these metrics, the overall process ensures not only reliable model assessment but also guards against overfitting, facilitating the model's adaptability to new, unseen data [104][109].

3.11.1.5 Evaluation metrics

Evaluation metrics are important to appraise the effectiveness of ML models. As machine learning progresses through the data processing pipeline, these metrics act as guiding indicators, assisting practitioners in refining models for optimal performance. In the context of regression analysis, metrics like MAE, MSE, and RMSE contribute nuanced insights into a model's accuracy. When delving into time-series analysis, Bayesian Information Criterion (BIC) assumes a role in guiding model selection, while MAPE and MASE provide essential perspectives in forecasting scenarios.

Mean absolute error (MAE):

MAE is the calculation of the average absolute differences between actual and estimated values (3.18).

$$\mathrm{MAE} = \frac{1}{\mathrm{N}} \sum |\mathrm{actual} - \mathrm{predicted}| \tag{3.18}$$

Mean squared error (MSE):

MSE represents differences between estimated average suared and actual average squared values (3.19).

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum (\mathrm{actual} - \mathrm{predicted})^2 \tag{3.19}$$

Root mean squared error (RMSE):

RMSE, derived from MSE, provides a comprehensible measure in the same unit as the target variable [103] (3.20).

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{3.20}$$

Bayesian information criterion (BIC):

Criterion metrics, such as BIC, gauge the goodness of fitting (GoF). Additionally, error metrics, including RMSE, are employed to quantify the model's error value. Moving forward, Bayesian Information Criterion (BIC) becomes integral in time-series analysis (3.21):

$$\mathrm{BIC} = \mathrm{n} * \log\left(\frac{\mathrm{SSE}}{\mathrm{n}}\right) + \mathrm{p} * \log(\mathrm{n}) \tag{3.21}$$

SSE represents sum of squared error (3.22) as:

$$\mathrm{SSE} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{3.22}$$

In addition to these time series-specific metrics, there are general metrics that offer a broader view of model performance. The Mean Squared Logarithmic Error (MSLE), formulated to handle datasets with exponential growth, provides an alternative to traditional Mean Squared Error (MSE). Furthermore, the R^2 score coefficient of determination gauges the proportion of the response variable's variance captured by the model, offering a comprehensive assessment of model performance across various domains. These metrics collectively contribute to a robust evaluation process, providing insights into different facets of model behavior.

Mean squared logarithmic error (MSLE):

MSLE is similar to MSE but works well for datasets with exponential growth (3.23).

$$\mathrm{MSLE} = \frac{1}{N}\sum(\log(\mathrm{actual} + 1) - \log(\mathrm{predicted} + 1))^2 \tag{3.23}$$

R^2 score:

Measures the proportion of the output variable's variance captured by the model (3.24).

$$R^2 = 1 - \frac{\sum(\mathrm{actual} - \mathrm{predicted})^2}{\sum(\mathrm{actual} - \mathrm{mean})^2} \tag{3.24}$$

4. EXPERIMENTAL WORK

In the realm of experimental work tailored for engine analysis, the initial step involved accessing and configuring the experimental setup, encompassing a dynamometer and a vehicle. This setup facilitated the collection of pertinent data, necessitating the incorporation of sensors, actuators, and dedicated data collection tools. The acquired data underwent a meticulous evaluation, followed by preprocessing to render it conducive to modeling.

The subsequent phase involved judiciously selecting input output parameters for the performance analysis, taking into account the type, quantity, and quality of the data. Decisions on the appropriate models were made based on this analysis. The architecture of the selected model was meticulously designed, with considerations given to the type of data and the overall model requirements. Software tools conducive to the model's deployment were also chosen.

The process continued with the creation of a tailored estimation model, finely tuned to the architectural nuances of the chosen model. Particular emphasis was placed on identifying suitable performance evaluation metrics, enabling a meaningful comparison between model predictions and real-world data. The interpretation of estimation performances was then derived from these comparative results.

Upon comprehensive evaluation of these processes, it became evident that the creation of a virtual model, closely aligned with reality, presented a cost-effective and time-efficient alternative. This virtual approach proved instrumental in tasks such as motor control, controller diagnosis, algorithm updates, and performance enhancements. This study embarked on a comprehensive exploration of various methods and engines, aiming to propose novel modeling approaches and discern the most fitting methodology among those present in the literature. The details and outcomes of each experiment are elucidated within the confines of this thesis, contributing to the advancement of knowledge in the field.

Four distinct investigations have been outlined to compare the machine learning and time-series methods identified in the context of the experimental work, as detailed in previous reports on the thesis progress. While these studies focus on diesel engines, including marine diesel engines, they have been extended to encompass a diverse engine for which data is obtained through a dynamometer. Consequently, it has been demonstrated that machine learning methods can robustly estimate by establishing a mathematical connection between collected data, irrespective of the engine's type, aligning with observations in existing literature.

- The initial study within the thesis involves employing ANN modeling to estimate performance and emissions based on data collected from a single-cylinder Wankel engine via a dynamometer.
- The second and pivotal study in the thesis entails a comparative application of various machine learning and time-series methods, distinct from those used in existing literature, on data gathered via a dynamometer from a 6-cylinder diesel engine suitable for medium-duty trucks and small-scale ship engines.
- Another study involves processing performance data collected during engine acceptance tests from a marine diesel engine. Time-series and selected machine learning methods from literature will be applied to these data. This study holds significance in the thesis for the insights gained from navigational test data collection.
- The fourth planned study aims to enhance the Wankel engine dynamometer, expanding the type and quantity of data specifically for performance and emission analysis. This extension leads to a broader array of machine learning methods to be applied, providing an opportunity to compare modeling methods used in the literature for similar data processing.

4.1 Modeling A Single Rotor Wankel Engine with ANN

Research on Wankel engines is notably scarce, representing a novel frontier in modeling and prediction. This study focuses on advancing the understanding of Wankel engines through ANN modeling. The primary goal is estimation of key parameters, including volumetric efficiency, power, and emissions like CO2, NOx, CO, and O2. The inputs for this ANN model encompass critical variables like the change of start of ignition angle, injection duration, mean effective pressure, and intake manifold pressure.

The experimental data utilized in this study is sourced from a comprehensive investigation conducted on a Wankel engine that shaped as a single rotor for testing purposes. It's noteworthy that the dataset is limited in size and exhibits variability across six different sets, each corresponding to distinct mean effective pressure values at constant revolution per minute as 3000 rpm. To evaluate the performance of the middle-speed range Wankel engine, the study employs the standard BPNN with Levenberg Marquardt algorithm. The outcomes affirm the efficacy of the ANN, demonstrating accurate estimation. The correlation coefficient (R) ranges between 0.79 and 0.97, indicating a strong agreement between the predicted and experimental data sets. This underscores the ANN model's capability to reliably capture the intricate dynamics of the Wankel engine under study.

4.1.1 Experimental setup

The experimental setup featured key components, including pressure evaluation device, brake, water cooler, fuel conditioning equipment, and gas analyzer.

Testing environment as dynomometer utilized for testing employed the Shenck W70 model electromagnetic engine brake, with dynamometer force being precisely measured using a load cell with a sensitivity of ± 0.02%. Various sensor information, including throttle position, and manifold pressures, was relayed to the sensor board. For experimental purposes related to modeling, the Wankel engine was adapted to a single rotor configuration. Detailed experiments have the potential to extend the dataset and facilitate the application of more advanced modeling approaches to enhance the understanding of this Wankel engine. The schematic view of Wankel experiment is shown Figure 4.1 and real test enivronment is shown in Figure 4.2.

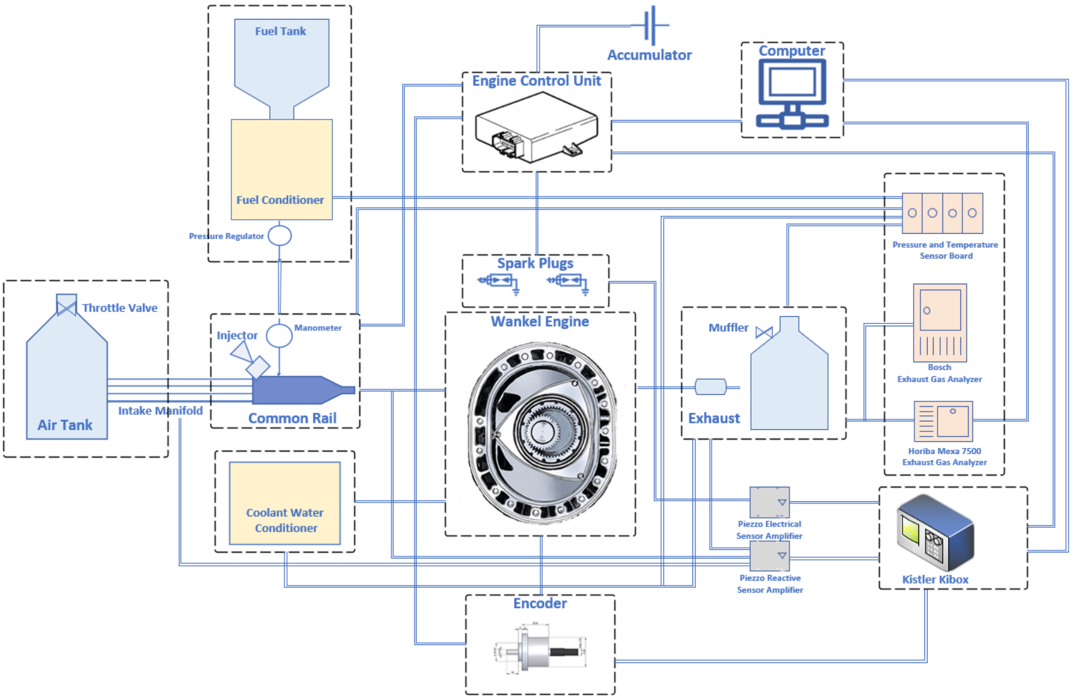

Figure 4.1 : Schematic view of Wankel engine experimental setup.

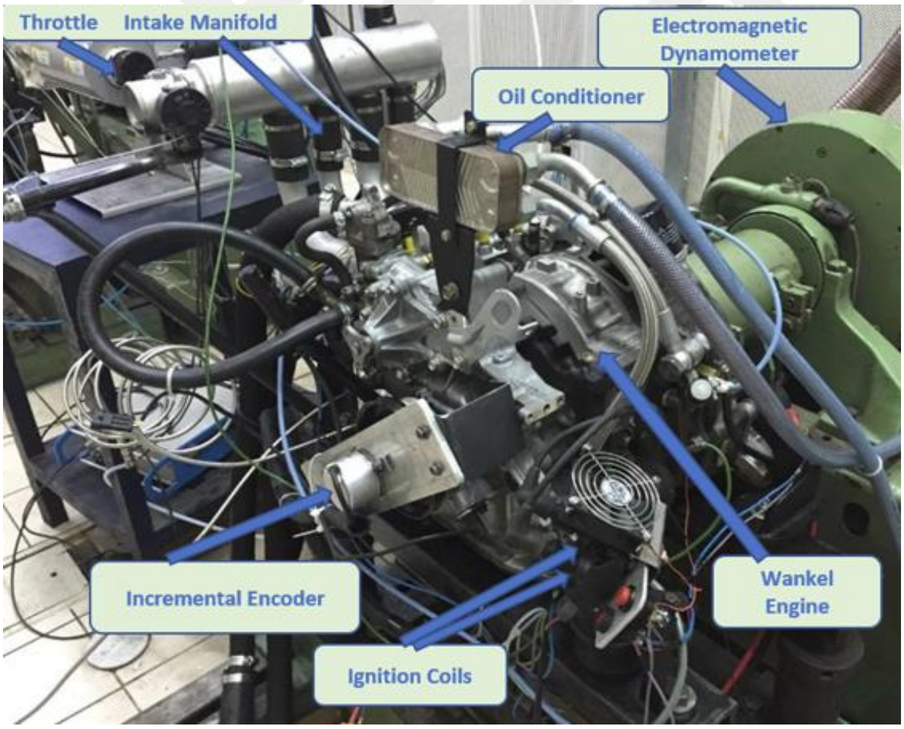

Figure 4.2 : Wankel engine test environment.

4.1.2 Neural network design

ANN gain prominence by utilizing simpler neuron units organized into high-performance structures. The core architecture of an ANN primarily comprises three essential layers: the input, hidden, and output layers. Input vectors carrying input information are initially placed in the input layer, then transmitted to the hidden layer for processing, ultimately producing the output vector. Each node relies on an activation function and can transmit signals from nodes in the previous layer.

The BPNN Levenberg Marquardt neural network algorithm is utilized to assess model performance. This algorithm integrates aspects of the Gauss-Newton and gradient descent, adapting its behavior based on the proximity of parameters to their optimal values.

In this study, the network model was constructed and trained using the MATLAB Neural Network Toolbox. Specifically applied to the Wankel engine, the ANN model is developed using data collected from the experimental setup. The model involves 70 percent of randomly selected data for training, 15 percent for performance testing, and the remaining 15 percent for validation. The backpropagation algorithm is chosen for weight calculation in the neural network.

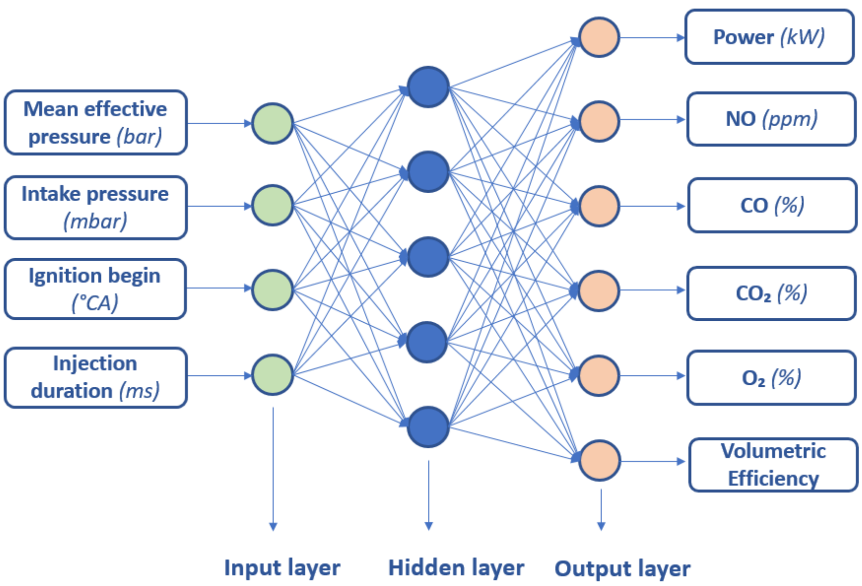

Figure 4.3 : BPNN network architeture.

Five hidden layers are chosen, while the output layer consists of six outputs related to performance and emissions, including power, NO emission, CO emission, CO2 emission, O2 emission, and volumetric efficiency. Network accuracy is evaluated using the R^2, which measures how effectively the regression line reflects actual data sets, ranging from 0 to 1. The back-propagation network architechture is represented in Figure 4.3.

4.1.3 Results and discussion

The estimation of Wankel engine performance within the mid-speed range was achieved through the application of the BP-ANN model utilizing the Levenberg Marquardt training algorithm within the Matlab Neural Network tool. The structure of the ANN model was configured with 4 inputs, 5 hidden layers, and 6 outputs. The network assessment utilized the R^2 criterion. A comprehensive evaluation of network response was conducted through regression analysis, comparing the network output with the corresponding targets. The outcomes affirmed that the model derived from the neural network was effective in forecasting the Wankel engine's performance within the mid-speed range, considering variations in mean effective pressure (ranging from 1 bar to 6 bar), intake manifold pressure, ignition timing, and injection duration. Comparative figures were presented, illustrating the match between experimental original data and estimation values for power, CO, CO2, NO, O2 emissions, and volumetric efficiency. Comparative estimation outputs are represented in Figure 4.4, Figure 4.5, and Figure 4.6 respectively.

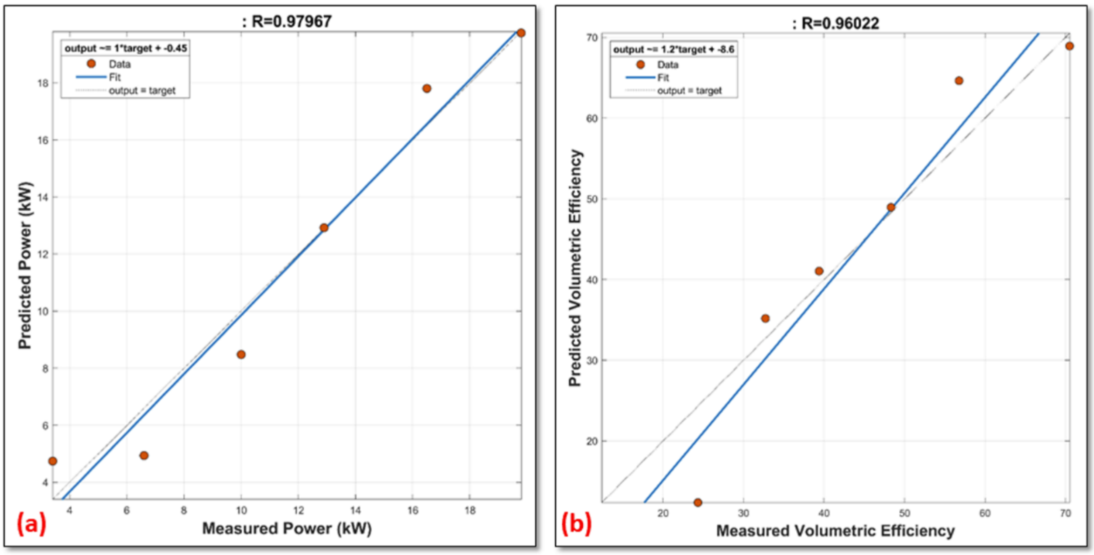

Figure 4.4 : Estimation performance for power (a) and volumetric efficiency (b).

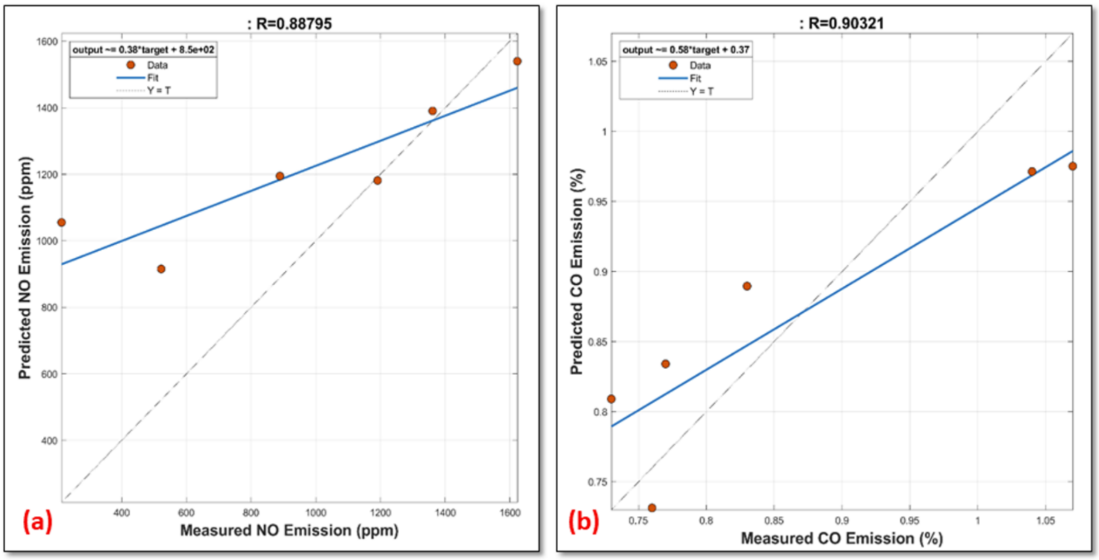

Figure 4.5 : Estimation performance for NO Emission (a) and CO Emission (b).

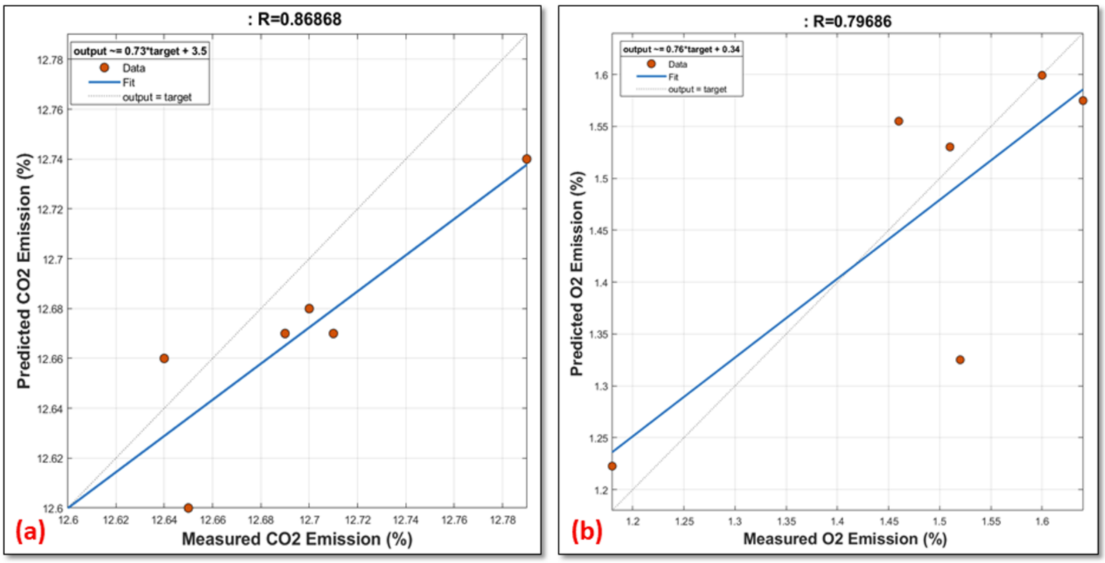

Figure 4.6 : Estimation performance for CO2 Emission (a) and O2 Emission (b).

Evaluation of the artificial neural network (ANN) estimation values for power, NO, CO, CO2, O2 and volumetric efficiency involved a thorough regression analysis, comparing the experiments and predicted outputs. Specifically, the correlation coefficients (R) for CO emission, CO2 emission, NO emission, O2 emission, volumetric efficiency, and power are 0.90321, 0.86868, 0.88795, 0.79686, 0.96022, and 0.97967, respectively.

These comparative analyses affirm that the artificial neural network model, constructed by discerning intake manifold pressure, mean effective pressure, ignition timing, and duration of injection effectively captures engine characteristics, even in instances with limited data sets. The outcomes provide evidence that the BPNN is proficient in prediction across varying intake manifold pressure, mean effective pressure, ignition timing, and injection duration within a consistent mid-speed range. Given the constraints of scarce data, the ANN performance is notably successful, particularly for volumetric efficiency and power outputs. However, there is room for comparative enhancement in emission-related predictions. Notably, for NO emission, which converges approximately 79%.

4.1.4 Conclusion

Initiating the application of ANN on Wankel engines, this study successfully created and trained an ANN model using six distinct and limited data points extracted from experimental results. Notably, this research marks the inaugural modeling of Wankel engine test outcomes using ANN, with no precedent found in existing literature.

The achieved correlation coefficients ranging from 0.79 to 0.97 signify commendable accuracy, particularly evident in power, volumetric efficiency, and CO emission estimations, where the correlation coefficient (R) exceeds 0.9, indicating a noteworthy 90% success rate in estimation. In a broader context, the prediction performance of the ANN model can be further enhanced through individual or combined implementation of the following measures:

- Augmenting data points: Increasing experimental results through additional tests
- Expanding features: Increasing the number and type of measured variables to better discern the relationship between outputs and inputs, thereby enhancing model generalization across all operational points.
- Enhancing and altering the algorithm to test the improvement capacity of predictions as model complexity increases.

Given the challenges faced by other mathematical or traditional modeling algorithms in converging real data for engine performance and emissions, particularly in light of its nonlinearity, the advantages of ANN—simplicity, speed, and accuracy—become apparent. This study underscores the compatibility and success of ANN algorithms in evaluating Wankel engine performance. With further enhancements to both the experimental setup and ANN modeling algorithms, these findings are poised to inspire subsequent studies and contribute to the modeling and control-based advancement of Wankel engines.

4.2 Modeling Performance and Emission of a Diesel Engine with Comparative Learning Techniques

This research delves into diverse intelligent time series modeling techniques, specifically the NARX, ARIMAX, MLR, and RegARMA. These methods are applied to a diesel engine to forecast NOx and fuel consumption. Experimental data is sourced from a six-cylinder turbocharged SCR, EGR and DOC equipped diesel engine with four-stroke and mid-duty truck level.

Model performance is meticulously scrutinized and assessed using BIC and RMSE criteria. The use of intelligent modeling methodology proves advantageous, offering highly accurate predictions and swift application capabilities for the analysis of internal combustion engine dynamics in control and calibration procedures, thereby mitigating the high costs and time constraints associated with experimental testing. In the comparative analysis of various modeling techniques, the RegARMA technique stands out, yielding a BIC value of 6707.6 with an RMSE of 105.58 for the NOx emission model, and a BIC value of 4026.4 with an RMSE of 7.93 for the fuel consumption model. Distinct datasets are processed independently to estimate NOx and fuel consumption. Input variables considered for evaluation encompass boost temperature and pressure, position of accelerator, coolant temperature, engine speed, load, engine torque, rail pressure, turbocharger speed and VGT position, EGR position and temperature, and exhaust gas pressure. MLR, NARX, ARIMAX, and RegARMA techniques are implemented separately on the datasets for NOx emissions and fuel consumption.

4.2.1 Input/Output selection and experimental setup

The judicious selection of input and output variables is a critical aspect that significantly influences the performance of machine learning models. The efficacy of these models in estimating complex phenomena, such as engine performance and emissions, relies heavily on the careful consideration and correlation of input features and the target output. The process of selecting inputs and outputs is akin to orchestrating a symphony, where each variable plays a distinct role in shaping the harmonious predictive capabilities of the model. The intricate relationships between these variables form the foundation upon which the model builds its understanding of the underlying patterns and dynamics. A meticulous choice of inputs, encompassing factors like exhaust gas recirculation (EGR) temperature, engine speed, and manifold air pressure, intricately linked with the target outputs, such as NOx emissions and fuel consumption, is paramount. This symbiotic relationship between inputs and outputs acts as the linchpin for achieving accurate and reliable estimations, underscoring the significance of thoughtful variable selection in the pursuit of effective machine learning model performance.

The primary objective of this endeavor is to formulate a comprehensive model for the generativity and emission behaviour of a diesel engine, specifically focusing on fuel consumption and NOx emission. The gathered input data are employed to predict these outcomes individually, given that certain inputs play a decisive role, even though several inputs exhibit a collective impact on both consumption (performance) and emission..

In the process of selecting appropriate inputs for data collection, the relationships have been assessed with reference to findings in existing literature. Yusaf et al. [91] provided insights into the variation in fuel consumption and NOx emission under different loads concerning boost temperature. Xin et al. [92] conducted an analysis of NOx emission reduction methods, noting the impact of EGR position and VGT position on fuel consumption and NOx emission. Choi et al. [93] delved into a novel cooling path control strategy, elucidating the interplay among coolant temperature, fuel consumption, and NOx emissions. Leahu et al. [94] observed the influence of exhaust gas temperature on engine performance and emissions. Damma et al. [95] explored the application of low-temperature SCR for NOx reduction, outlining how SCR utilization in diverse temperature conditions affects NOx emissions. Colban and Miles [96] demonstrated the advantages of increasing boost temperature, resulting in reduced NOx emissions and enhanced combustion efficiency. Figure 4.7 illustrates the engine specifications and the diesel engine diagram equipped with additional the exhaust system.

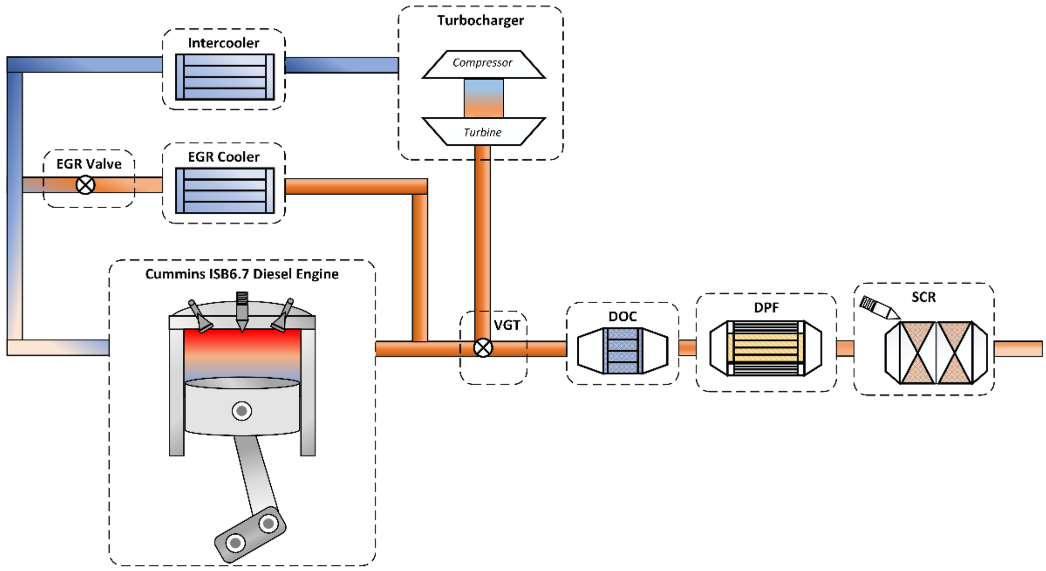

Figure 4.7 : Diesel engine schematic with aftertreatment system.

The variation in data collected from the sensors that equipped to the control unit has been meticulously processed to encompass diverse working modes during engine operation. The classification of engine control algorithm working modes is contingent upon the method of torque calculation, facilitating the collection of a broad spectrum of data.

4.2.2 Time series modeling techniques

The behavior of systems, influenced by temporal changes, is notably reliant on prior outputs due to the inherent relationship among data. This characteristic introduces a challenge in modeling due to the pronounced non-linearity. Unlike different type of non-linear methodologies, previous or even elder data play a crucial role in establishing connections for predicting subsequent responses. Consequently, the modeling of time based or dependent systems necessitates additional approximators, such as RNNs, compared to other non-linear systems. Additionally, generic and mostly used type methods like FFNNs can be adapted for time based systems with enhanced efficiency. Techniques like RegARMA, MLR, ARIMAX, NARX or NLARX acknowledged as various methodologies capable of predicting outputs with multiple inputs, are selected for estimating the fuel consumption and NOx emission outputs of the diesel engine. NARX schematic is shown in Figure 4.8.

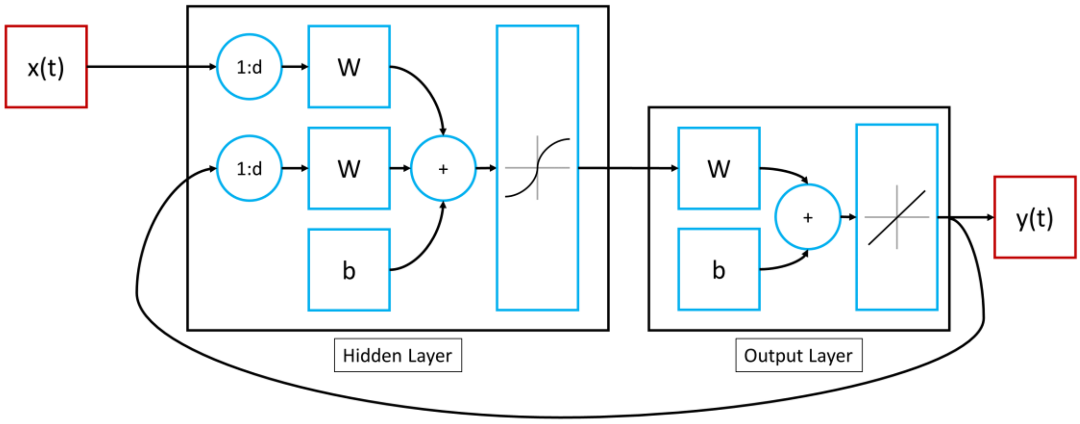

Figure 4.8 : NARX schematic.

4.2.3 Evaluation metrics

Evaluation metrics are employed to gauge the model's effectiveness and drive enhancements in prediction accuracy. However, when evaluating the performance of time series models, additional metrics are required compared to non-time series techniques. Time series data inherently involves a relationship between each sample and its preceding and succeeding samples. Information criterion metrics, such as the BIC, are utilized to gauge the goodness of fitting (GoF). Additionally, error metrics, including the RMSE, are employed to quantify the model's error value. In this study, BIC serves as the time series metric, while RMSE is harnessed to compute the model's error value. Both metrics indicate that a lower value corresponds to a better fit for the models.

4.2.4 Discussion of results

In this section, the efficacy of time series techniques is assessed using metrics and juxtaposed, as depicted in Figure 5. BIC is employed for GoF assessment in time series models, while RMSE serves the purpose of error calculation. Presenting the evaluation outcomes, the NOx estimation corresponds to a BIC of 6918.4 and an RMSE value of 94.03 for the NARX model, 9616.7 BIC and 147.7 RMSE for the MLR model, 6753.7 BIC and 105.69 RMSE for ARIMAX, and 6707.6 BIC and 105.58 RMSE for RegARMA. In the comparison, the NARX model exhibits the lowest RMSE, whereas MLR has the highest RMSE. The other metrics align more closely with NARX. Regarding BIC, MLR again demonstrates the lowest performance with the highest BIC value, attributed to its simple background lacking lag polynomials. ARIMAX and RegARMA have closely aligned BIC values, but RegARMA slightly outperforms ARIMAX. Despite ARIMAX and RegARMA showing adequate but not optimal performance in terms of RMSE due to their reliance on auto-regressive and moving average methods, RegARMA leads in modeling NOx with the lowest BIC and satisfactory RMSE, as illustrated in Figure. Fuel consumption modeling presents a unique challenge due to significant spikes in time series data. The NARX model yields a BIC of 4239.9 and an RMSE of 6.35, while MLR results in a BIC of 4792.9 and an RMSE of 5.75. Meanwhile, ARIMAX records a BIC of 4240.0 and an RMSE of 7.9386, and RegARMA yields 4026.4 BIC and 7.9310 RMSE. Consequently, MLR exhibits the lowest and thus the best RMSE performance but, conversely, the highest BIC, indicative of the lowest time series performance. RegARMA, as a time series technique, stands out with the lowest BIC, with ARIMAX closely following its performance. Examination of the results reveals that RegARMA boasts the highest estimation performance, closely followed by ARIMAX on average. Despite this, the higher RMSE values for RegARMA and ARIMAX result from these modeling techniques employing auto-regressive and moving-average methods, introducing shifts in the models. The model fits are depicted with experimental data represented by the red line in Figure 4.9 and Figure 4.10 for NARX, Figure 4.11 and Figure 4.12 for MLR, Figure 4.13 and Figure 4.14 for ARIMAX, and Figure 4.15 and Figure 4.16 for RegARMA, corresponding to NOx and fuel consumption, respectively.

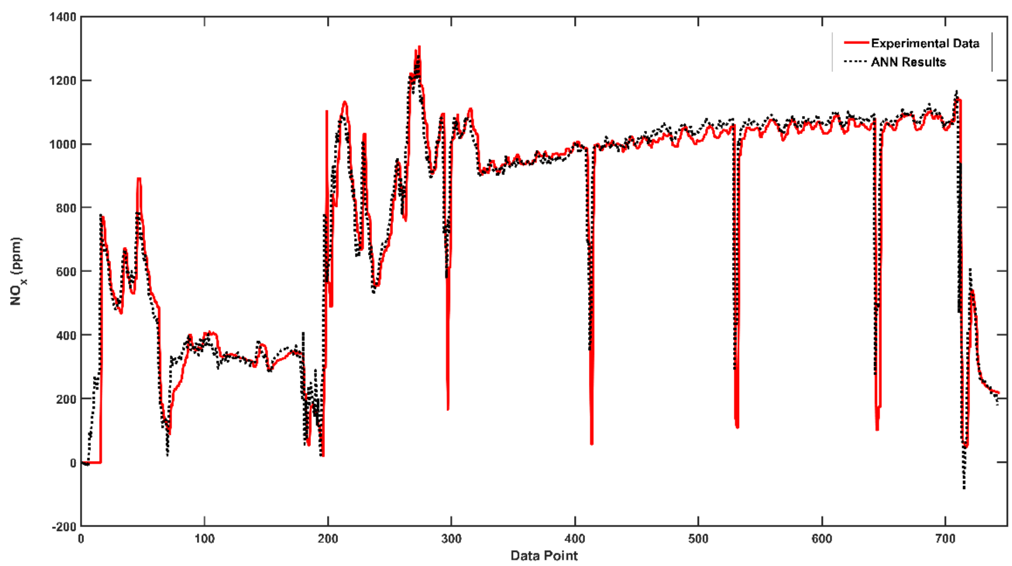

Figure 4.9 : NARX model prediction comparison for NOx.

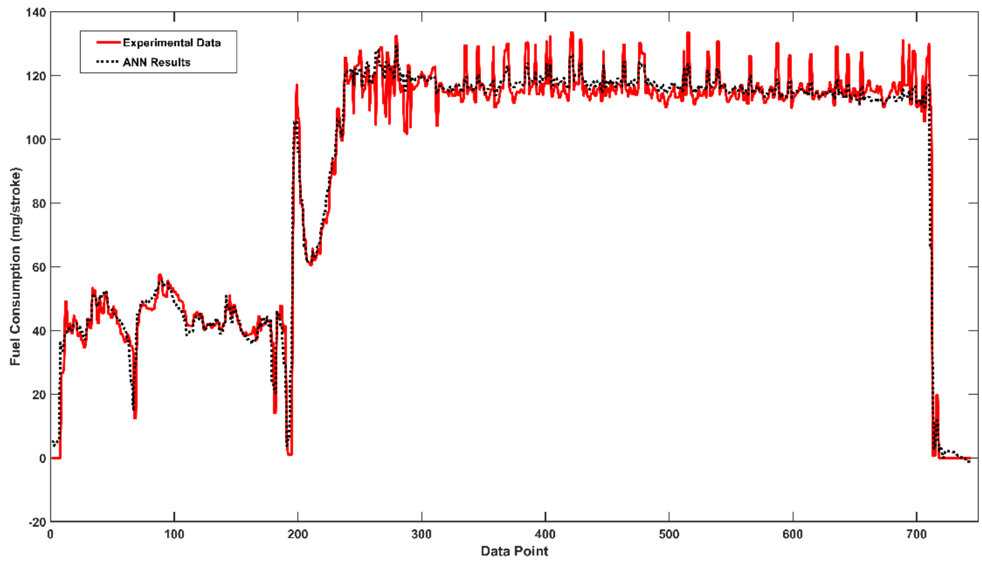

Figure 4.10 : NARX model prediction comparison for fuel consumption.

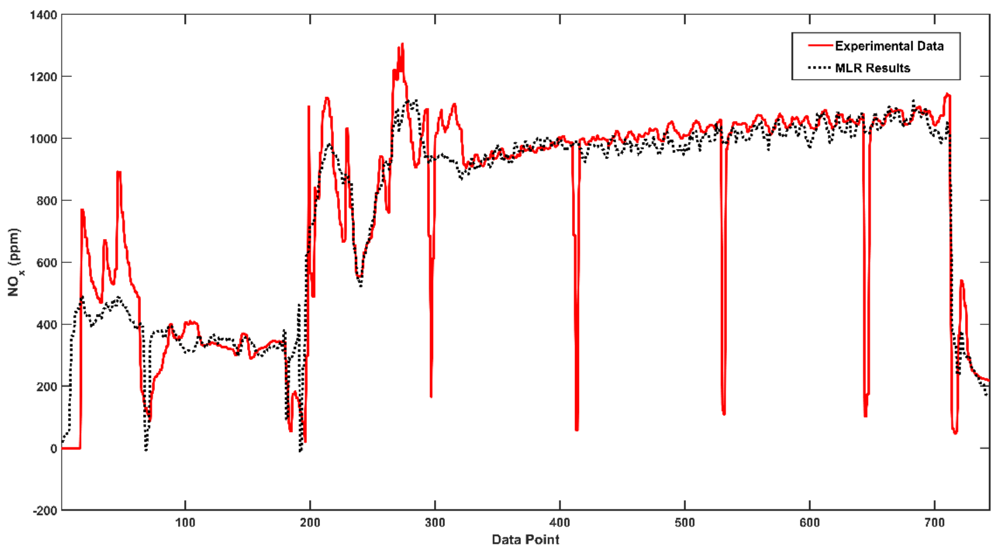

Figure 4.11 : MLR model prediction comparison for NOx.

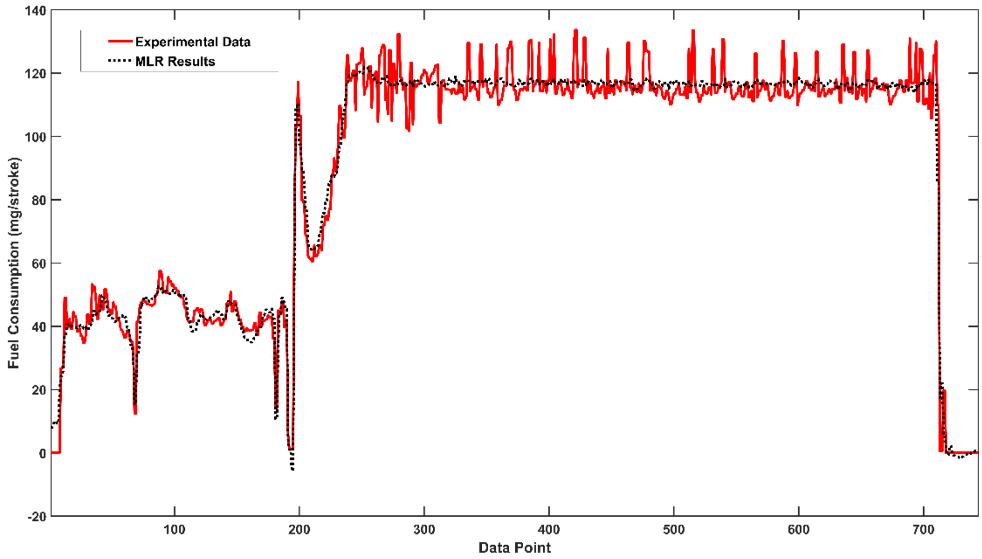

Figure 4.12 : MLR model prediction comparison for fuel consumption.

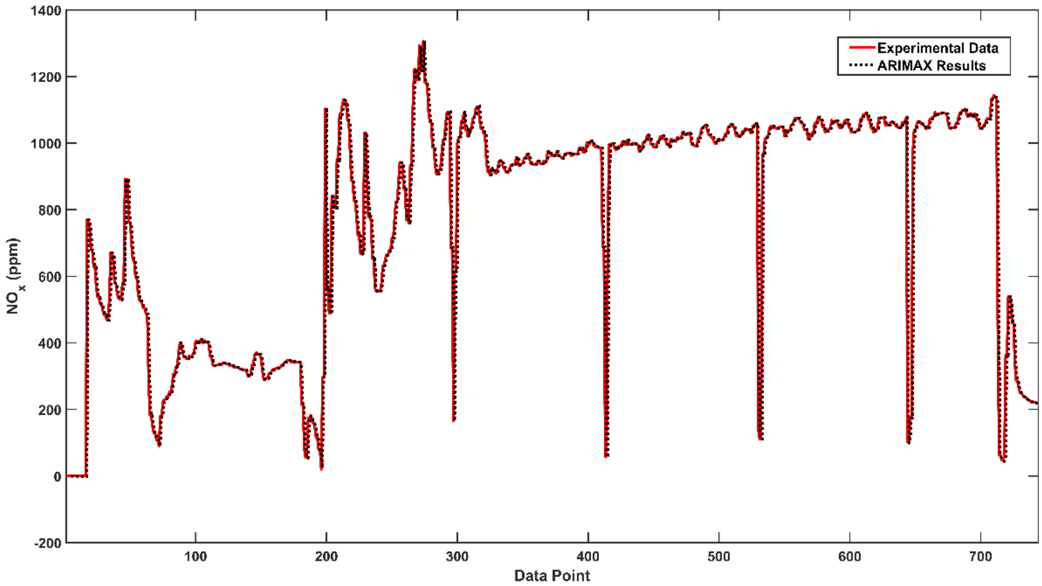

Figure 4.13 : ARIMAX model prediction comparison for NOx.

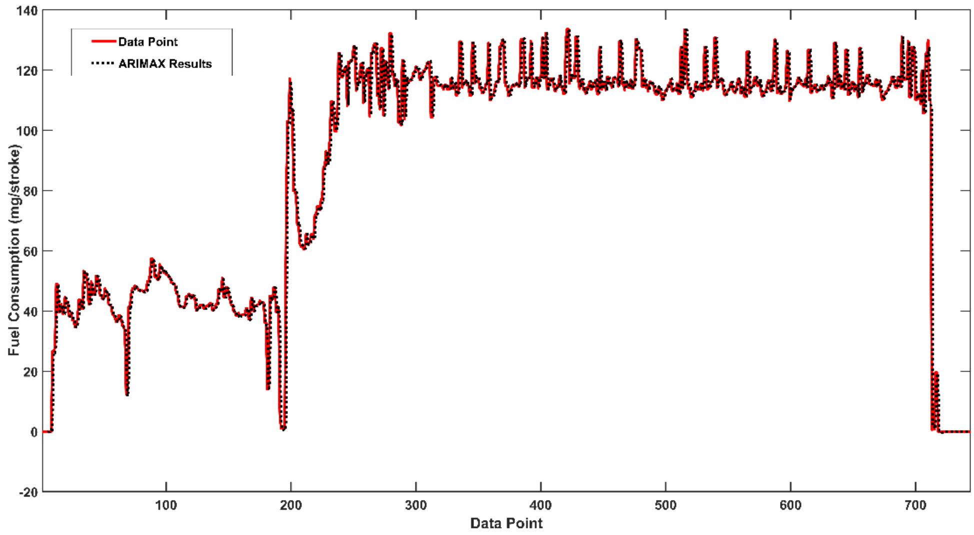

Figure 4.14 : ARIMAX model prediction comparison for fuel consumption.

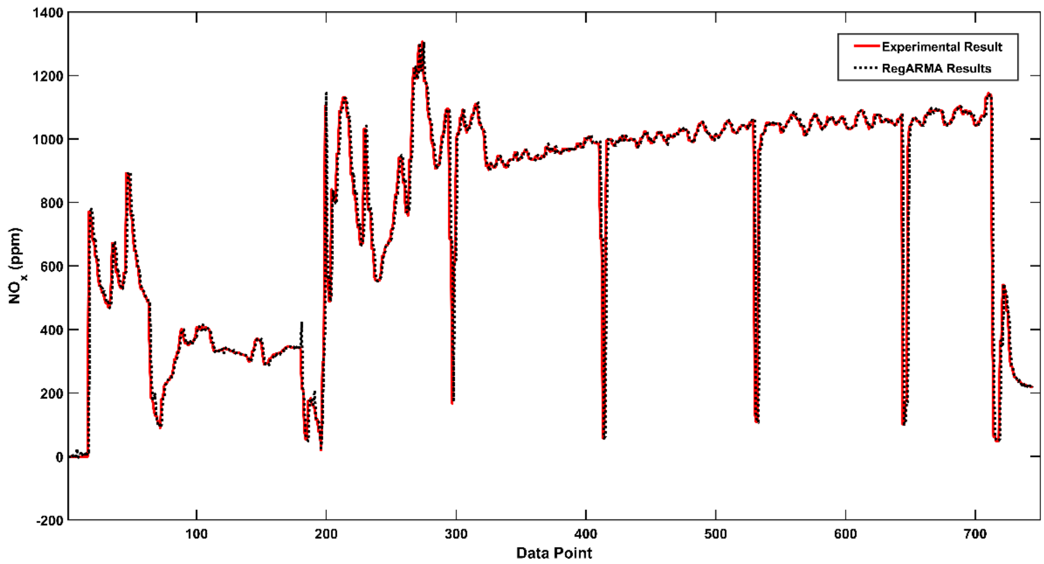

Figure 4.15 : RegARMA prediction comparison model for NOx.

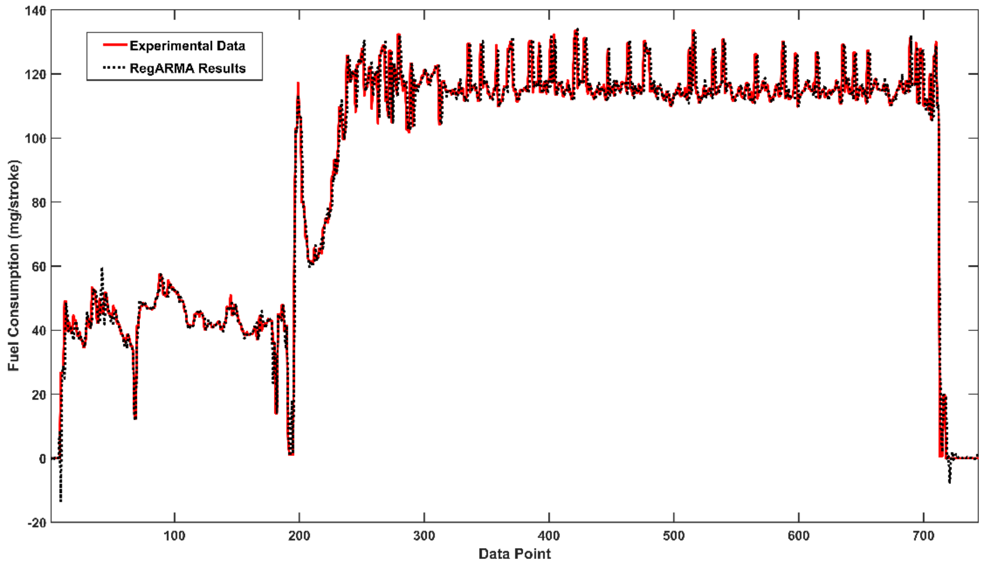

Figure 4.16 : RegARMA model prediction comparison for fuel consumption.

4.2.5 Conclusion

The primary objective of this investigation is to delineate and contrast the efficacy of diverse data-driven time series modeling techniques employed for forecasting the crucial variables—fuel consumption and NOx emission—in a diesel engine. The empirical data are derived from a medium-duty diesel engine integrated into a passenger bus. Utilizing NARX as an artificial neural network, alongside MLR, ARIMAX, and RegARMA as time series methodologies, we systematically apply these models to a comprehensive dataset collected during various operation modes in the engine-bus integration tests. The significance of input variables is scrutinized to ensure their appropriateness for the chosen output variables. encompass boost temperature and pressure, position of accelerator, coolant temperature, engine speed, load, engine torque, rail pressure, turbocharger speed and VGT position, EGR position and temperature, and exhaust gas pressure are selected as inputs for estimating fuel consumption and NOx emission. All time series modeling techniques effectively capture the relationships between inputs and outputs. To assess and compare model performance, BIC and RMSE evaluation metrics are employed. In the comparative analysis, RegARMA emerges as the frontrunner, yielding a BIC of 4026.4 and an RMSE score of 7.93 for fuel consumption, while recording 6707.6 BIC and 105.58 RMSE for NOx emission. Given the cost and time constraints associated with experimental tests, the sequential implementation of time series methods proves successful in predicting output variables, facilitating the comprehensive analysis of diesel engine performance and emissions. In conclusion, leveraging a diverse dataset, time series methods offer swift and accurate solutions for modeling the behaviour of a diesel engine.

5. CONCLUSIONS AND RECOMMENDATIONS

This study aimed to contribute to the advancements in diesel engine technology within an industry facing rising expectations and environmental constraints amid the growing prevalence of electric commercial vehicles. To address the challenges of controlling parameters influencing emission and performance for a ship diesel engine, a virtual environment, closely mirroring reality, was created. This virtual setting allowed testing controllers without the necessity for real-time, expensive, and time consuming tests. Data-driven modeling methods, serving as alternatives to traditional testing, were employed to develop a simulation. The study delved into the working principles of diesel and ship diesel engines, identifying critical control parameters, exploring frequently used and less-preferred modeling methods in the literature, and comparing these methods based on specific criteria aligned with the collected data's characteristics.

Initiating with data collection from a Wankel engine connected to a dynamometer, ANN modeling was conducted, marking the inception of machine learning and artificial intelligence applications. This study, which is the first study related to the thesis, was published in the This study, which is the first study related to the thesis, was published in a local journal.

- The plan involved gathering additional data from the Wankel engine to extend the modeling study, encompassing comparative methods. Simultaneously, efforts were made to assess the estimation capabilities of machine learning methods across different engine types with non-linear features and distinct operating principles. However, this endeavor faced challenges in processing the collected data and obtaining diesel engine data simultaneously, leading to its incomplete status.

As a pivotal point in the thesis, data was acquired from an industrial-grade diesel engine, typically found in medium-duty trucks or light-duty boats, connected to a dynamometer. Focused on engine acceptance tests, the evolving nature of the collected data over time allowed the modeling of the engine using prevalent time-series methods in statistical modeling literature. The comparison involved these methodologies and an ANN-based modeling approach. The study identified the RegARMA modeling method as the optimal choice. The findings of this research were subsequently published in IEEE Access, an international journal.

- To explore and compare more methods encountered in the literature practically, data collection was planned from the diesel generator of a ferry docked at Sefine shipyard during acceptance tests. However, simultaneous theoretical and practical applications, coupled with time constraints, impeded the swift processing and modeling of the collected data, rendering this study incomplete.

In conclusion, this thesis presented multiple studies, serving as a comprehensive literature review for both ship diesel engines and machine learning. These studies aimed to support emission and performance analysis and have been meticulously incorporated into the thesis.

As a recommendation, the continuation of this work involves processing and modeling the collected data from both the Wankel engine and the ship diesel engine, utilizing the mentioned methods suitable for the data, and comparing the results. Furthermore, there's potential for automating the use of these modeling methods and developing tools for such automation. The integration of engine models into a real-time loop (HiL or dynamometer) can facilitate improvements in control algorithms and calibration, minimizing losses in prolonged testing processes that demand substantial investments. This comprehensive approach contributes to addressing industry challenges and analyzing performance in the face of increasing emission restrictions.

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CURRICULUM VITAE

Name Surname : Mehmet İlter ÖZMEN

EDUCATION :

- **B.Sc.** : 2010, Istanbul University, Enginering Faculty, Mechanical Engineering
- **M.Sc.** : 2015, Istanbul Technical University, Graduate School, Mechatronics Engineering

PROFESSIONAL EXPERIENCE AND REWARDS:

- 2016 Tumosan Co. Control System Engineer Theoretical Physics.
- 2017 AVL Control System Engineer
- 2019 Ecemtag Co. Control System Team Leader
- 2022 TOGG Co. Powertrain System Engineer

PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- **ÖZMEN, M. İ., CİHAN, Ö., KUTLAR, A., ÖZSOYSAL, O. A., & Baykara, C.** 2020: Modelling A Single-Rotor Wankel Engine Performance With Artificial Neural Network At Middle Speed Range. *International Journal of Automotive Science And Technology*, *4*(3), 155-163.

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