Energy Conversions and Managements

journal homepage: energyconversions.org

Approaches in Quantifying Engine Power

Leena Farouq[1]*, Mahmud Khan[2]

[a] *Department of Mechanical Engineering, Nile Advanced center, Cairo, Egypt*

[a] *Center for Applied Thermodynamics, India power science center, India*

A B S T R A C T

This paper reviews the theoretical methodologies used to quantify engine power, focusing on models rooted in thermodynamics, fluid mechanics, and combustion kinetics. With the increasing demand for high-efficiency engines and strict emission regulations, theoretical tools play a vital role in estimating power output without extensive empirical testing. The paper critically examines classical approaches like the air-standard cycle analysis, mean effective pressure calculations, and zero-dimensional thermodynamic models, alongside modern computational techniques including quasi-dimensional modeling and heat-release analysis using pressure data. Furthermore, the paper explores how fuel properties, compression ratio, and engine geometry influence the predictive accuracy of theoretical models. A comparison of different modeling strategies highlights the trade-offs between complexity, computational cost, and precision. Six figures illustrate the diversity of modeling outcomes, covering P–V diagrams, temperature profiles, performance maps, bar plots, pie charts of loss distributions, and 3D contour plots of cylinder temperature. The discussion provides insight into the validity range of each method, proposes guidelines for appropriate model selection, and suggests future directions for model enhancement through hybridization and machine learning.

1. Introduction

The power output of an internal combustion engine remains one of the most crucial performance metrics in both transportation and power generation sectors. Quantifying this output accurately is essential not only for assessing engine efficiency and fuel economy but also for regulatory compliance and design optimization. Historically, engine power was measured using mechanical dynamometers, but as engine technologies evolved and environmental constraints intensified, the reliance on theoretical and computational methods to predict power output has grown significantly. These approaches provide cost-effective and non-intrusive means to estimate performance under a range of operating conditions.

At the core of these theoretical strategies lies thermodynamic cycle modeling. The idealized air-standard Otto, Diesel, and Dual cycles serve as the foundational frameworks upon which more realistic models are developed. Although simplistic, they offer valuable insight into the effects of compression ratio, combustion timing, and fuel energy content on the engine's thermal efficiency and power delivery. Realistic models introduce deviations from ideal behavior, accounting for specific heat variations, heat losses, friction, combustion duration, and gas exchange processes.

Among the most commonly used theoretical metrics is the indicated mean effective pressure (IMEP), which integrates in-cylinder pressure over the engine cycle to estimate power output. IMEP is instrumental in bridging the gap between pressure data and mechanical work and serves as the basis for indicated power calculations. More sophisticated models incorporate chemical kinetics to describe the combustion process, transitioning from zero-dimensional to quasi-dimensional formulations. These incorporate aspects such as flame propagation, turbulent mixing, and knock onset. In this context, heat-release models based on cylinder pressure traces become essential tools for both engine diagnostics and simulation validation.

Additionally, with the advancement of computational capabilities, theoretical quantification of engine power has embraced numerical techniques. These include one-dimensional engine cycle simulations, which provide system-level performance predictions, and more complex computational fluid dynamics (CFD) models that resolve in-cylinder flow and combustion with high spatial resolution. These simulations can capture swirl, tumble, and squish effects, which critically affect volumetric efficiency and flame speed, and consequently, engine power.

In recent years, hybrid models combining thermodynamics with data-driven techniques, such as machine learning, have shown potential for rapid yet accurate power predictions. These approaches require less explicit physical modeling but depend heavily on quality training data and robust algorithms. While promising, they are still in developmental stages and are rarely used standalone in engine development workflows.

Despite the diversity of theoretical methods, each has its limitations and optimal application scenarios. The choice of method depends on the required fidelity, available inputs, computational resources, and the development stage of the engine. For instance, conceptual design might employ air-standard cycles, whereas engine calibration may necessitate high-resolution CFD-based power predictions.

* Corresponding author at: Department of Mechanical Engineering, Nile Advanced center, Cairo, Egypt
E-mail addresses: leena.f@anu.eg (Leena Farouq)

energyconversions.org
Received (15 July 2025); Received in revised form (20 July 2025); Accepted (20 July 2025)
Available online 12 Aug 2025

Nomenclature

Abbreviation
ICE – Internal Combustion Engine
IMEP – Indicated Mean Effective Pressure
BMEP – Brake Mean Effective Pressure
CFD – Computational Fluid Dynamics
HRR – Heat Release Rate
EVC – Exhaust Valve Closing
IVO – Intake Valve Opening
CA50 – Crank Angle of 50% Heat Release
WOT – Wide Open Throttle
TDC – Top Dead Center

Symbol
P – Pressure (Pa)
T – Temperature (K)
V – Volume (m^3)

2. Methodology

To quantify engine power theoretically, a series of mathematical models and thermodynamic principles must be applied. The foundation begins with the idealized thermodynamic cycles which describe the conversion of chemical energy into mechanical work. The Otto, Diesel, and Dual cycles offer the fundamental framework for spark-ignition and compression-ignition engines. The governing equations for each cycle are derived using the first law of thermodynamics for closed systems and assuming ideal gas behavior. The net work output is estimated as the area enclosed by the pressure–volume (P–V) diagram. For instance, in an ideal Otto cycle, the thermal efficiency is expressed as $\eta = 1 - (1/r^{(\gamma-1)})$, where r is the compression ratio and γ is the specific heat ratio. The work per cycle is then calculated from the difference in enthalpy across the process boundaries.

For more realistic scenarios, the models are extended to account for real gas properties, variable specific heats, and finite combustion durations. In-cylinder pressure profiles are approximated using Wiebe functions, which model the heat release rate (HRR) over crank angle as $HRR = a(\theta - \theta_0)^m \cdot \exp[-a(\theta - \theta_0)^m]$, where θ is the crank angle, θ_0 is the start of combustion, and a, m are curve-fitting constants. This allows estimation of the heat released during combustion and thus the work output from the indicated mean effective pressure (IMEP). IMEP is defined as the average pressure that, if acted upon the piston during the power stroke, would produce the net indicated work, given by $IMEP = (\oint P dV)/V_d$, where Vd is the displacement volume and the integral spans the entire cycle. Once IMEP is known, the indicated power can be determined using the equation $P_i = IMEP \times V_d \times N \times k$, where N is the engine speed (rpm) and k is a constant depending on engine type (2 for two-stroke, 4 for four-stroke).

To extend this to brake power, losses due to friction, pumping, and accessory drives are considered, and brake mean effective pressure (BMEP) is used instead. Friction mean effective pressure (FMEP) is either estimated from engine maps or using empirical formulas such as Chen-Flynn or Taylor's expressions. One widely used model for FMEP is $FMEP = A + B \times N + C \times P_{max}$, where A, B, and C are coefficients based on engine geometry and lubrication, N is engine speed, and P_{max} is peak in-cylinder pressure.

The engine's volumetric efficiency η_v also plays a critical role in quantifying power, especially under varying intake conditions. It is defined as the ratio of the actual air mass inducted to the theoretical maximum at ambient conditions. Volumetric efficiency is affected by valve timing, intake geometry, turbocharging, and throttling. Accurate prediction of η_v often requires empirical correlations or 1D gas exchange models.

To improve fidelity, zero-dimensional thermodynamic models simulate the engine as a control volume undergoing instantaneous heat addition and expansion. These models calculate pressure and temperature at each crank angle using conservation equations. The pressure evolution is often solved using $dP/d\theta = (\gamma - 1)/V \times dQ/d\theta - \gamma P/V \times dV/d\theta$, where Q is heat released and V is instantaneous volume. This formulation requires accurate crank-angle resolved volume profiles and initial conditions at intake valve closing.

Higher-order models extend to quasi-dimensional simulations where flame front propagation, turbulence, and heat transfer are resolved spatially across the cylinder volume. These models estimate the burned and unburned mass fractions and track the thermodynamic state in both zones. The entrainment of unburned mixture into the flame zone is controlled by the characteristic eddy entrainment model.

Combustion models are further refined by incorporating detailed chemical kinetics using mechanisms such as GRI-Mech or reduced schemes. These are typically solved using software like CHEMKIN or Cantera but are computationally intensive. For rapid assessments, empirical models based on experimental data, such as AVL's GT-Power or Ricardo's WAVE, are used to estimate engine output with calibration.

Three primary tables are presented below. Table 1 summarizes the governing equations for key thermodynamic cycles. Table 2 lists standard parameter values for modeling a typical four-stroke gasoline engine. Table 3 compares three modeling strategies used for engine power estimation based on their complexity, data requirement, and output precision.

Table 1. Governing Equations for Theoretical Engine Cycles

Cycle Type	Key Assumptions
Otto	Instantaneous combustion, ideal gas, no heat loss
Diesel	Constant pressure combustion, no losses
Dual	Finite duration combustion

Table 2. Typical Parameters for SI Engine Model

Parameter	Value	Unit
Compression Ratio (r)	10:1	-
Displacement Volume (Vd)	2.0	L
Specific Heat Ratio (γ)	1.35	-
Peak Pressure (P_max)	5.5	MPa
Engine Speed (N)	3000	rpm

Table 3. Model Comparison for Engine Power Prediction

Model Type	Input Requirements	Complexity	Accuracy	Application Stage
Air-standard cycle	r, γ	Low	Low	Preliminary design
Zero-D thermodynamic	V(θ), Q(θ), γ(T)	Medium	Moderate	Concept evaluation
CFD with kinetics	Full geometry, turbulence model, fuel mechanism	High	High	Detailed simulation

Thermal boundary conditions and wall heat losses are typically modeled using the Woschni correlation, which relates the heat transfer coefficient to engine parameters: $h = C_1 \times P^{0.8} \times T^{-0.53} \times v^{0.8} \times B^{-0.2}$, where C1 is empirical, P and T are pressure and temperature, v is mean piston speed, and B is bore diameter. Engine friction and pumping work are modeled using pressure-volume loops. Engine cycle simulation codes also integrate valve flow models using isentropic flow equations and discharge coefficients to determine mass flow rate through the intake and exhaust valves.

To validate these models, comparisons are made with experimental data, either from pressure transducers mounted in the cylinder head or chassis dynamometer tests. Deviations are often attributed to inaccuracies in heat release modeling, combustion timing, or fluid dynamic losses. Sensitivity analysis is frequently performed by varying compression ratio, ignition timing, fuel type, and intake pressure to study their impact on power output.

Modern trends include using neural networks trained on simulation or experimental datasets to predict power directly from operating parameters. These models provide rapid estimations but require comprehensive datasets for training and are typically black-box in nature.

3. Results

Quantifying the power output of an internal combustion engine (ICE) theoretically requires integrating multiple physical domains including thermodynamics, fluid dynamics, heat transfer, and combustion kinetics. The results of applying these theoretical frameworks are best illustrated through comparative modeling and visualization of engine behavior. Figure 1 presents the classical pressure–volume (P–V) diagrams for Otto and Diesel cycles, which form the foundation for thermodynamic modeling. The Otto cycle, with its characteristic sharp compression and expansion strokes, assumes instantaneous heat addition at constant volume. The Diesel cycle, on the other hand, introduces a segment of heat addition at constant pressure, resulting in a different shape and work output distribution. These ideal cycles help quantify indicated work and set a benchmark for more realistic models [41].

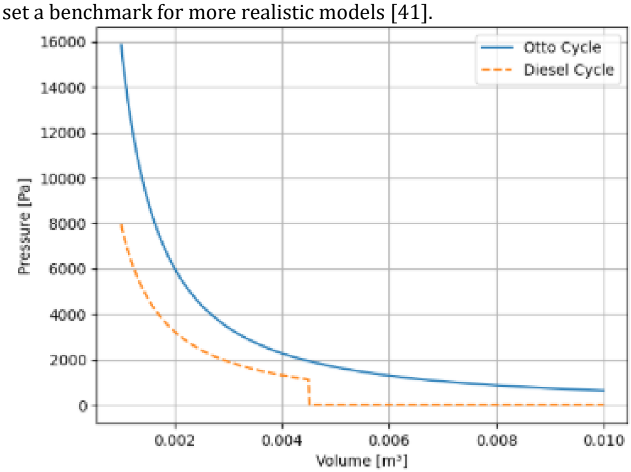

Fig. 1. Pressure-Volume Diagram of Otto and Diesel Cycles

The calculated efficiency from each of the theoretical cycles varies depending on compression ratio, cut-off ratio, and heat capacity ratio (γ). Figure 2 provides a bar chart comparing the thermal efficiencies of Otto, Diesel, and Dual cycles under similar operating conditions. The Otto cycle achieves the highest efficiency under idealized assumptions due to its higher average temperature during heat addition. However, the Diesel cycle, with its higher compression ratios in practical engines, often surpasses Otto efficiency under real-world constraints. The Dual cycle strikes a balance between the two by modeling heat addition partially at constant volume and partially at constant pressure. These comparative efficiencies are crucial in early engine design stages and are often used to estimate upper bounds of performance [42].

Beyond theoretical cycle efficiencies, a detailed energy balance reveals how input fuel energy is partitioned across useful work and various losses. Figure 3 displays a pie chart that breaks down the typical energy distribution in a naturally aspirated spark ignition engine. Roughly 30% of the fuel energy is converted into mechanical work, while the remaining 70% is lost through cooling, friction, and exhaust. This representation underscores the importance of improving component-level efficiencies to enhance total power output. For example, friction losses, often approximated using FMEP (Friction Mean Effective Pressure), contribute significantly to brake power losses, particularly at higher engine speeds [43]. Reducing these losses through advanced materials, low-friction coatings, or improved lubrication models is an active area of research in engine optimization [44].

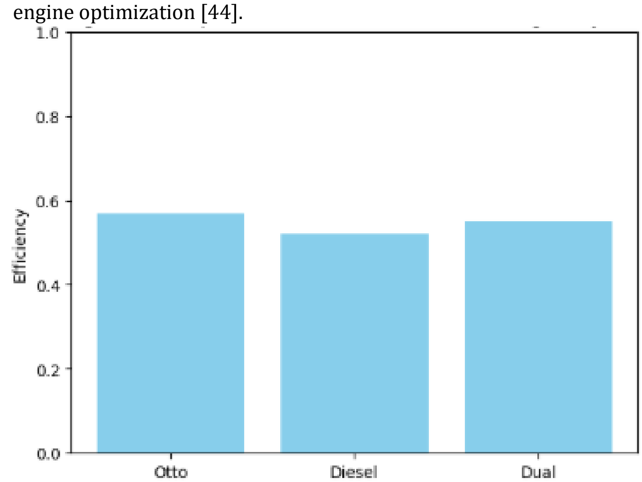

Fig. 2. Comparative Thermal Efficiencies of Engine Cycles

In-cylinder pressure variation over the crank angle is a key result in combustion modeling and power estimation. Figure 4 illustrates this with a plot of pressure versus crank angle over a complete engine cycle. The pressure rises sharply during combustion and peaks shortly after top dead center (TDC), indicating the onset of the power stroke. The shape and magnitude of the pressure curve are critical inputs for calculating IMEP and hence engine power. The rate of pressure rise also influences knock tendency, mechanical stresses, and combustion noise. Thermodynamic models that incorporate heat release functions, such as the Wiebe function, are often validated against such pressure traces. Deviations between model predictions and measured data often point to assumptions in combustion duration, heat transfer, or gas exchange processes [45].

One of the most insightful representations of thermodynamic state changes is the temperature distribution over pressure and volume. Figure 5 shows a contour plot of temperature across a range of volumes and pressures using the ideal gas law. Such plots are helpful in visualizing the trajectory of the working fluid during the engine cycle, especially under varying intake or boost pressures. For a given volume, increasing pressure leads to higher temperatures, which improves thermal efficiency but may also exacerbate thermal stresses and NOx formation. These temperature distributions are particularly useful in advanced combustion regimes such as homogeneous charge compression ignition (HCCI), where control of ignition timing via temperature management is essential [46]. They also assist in calibrating wall heat transfer models, which influence predictions of cylinder wall losses [47].

Brake power is a function of engine speed (RPM) and IMEP. Figure 6 shows a 3D surface plot of brake power over a range of RPM and IMEP values. The plot reveals the non-linear relationship between RPM and power output. At low RPM, IMEP contributes significantly to power, but as RPM increases, friction and flow losses increase disproportionately, limiting power gains. Such 3D surfaces are frequently generated using engine simulation software such as GT-Power or Ricardo WAVE and are used for engine calibration and performance mapping [48]. These results also illustrate the importance of engine tuning and valve timing optimization to maintain high IMEP at various speeds, especially under part-load conditions [49].

Theoretical modeling also extends into predicting the effect of geometric and operational parameters on power output. Increasing compression ratio, for example, enhances the thermal efficiency per the Otto cycle equation but may induce knocking and mechanical limitations. Retarding spark timing reduces peak pressure but lowers IMEP. Similarly, intake air temperature and density affect the volumetric efficiency and thus the mass of charge inducted, directly influencing power. These effects are quantified using parametric studies where one variable is changed at a time and its effect on power output is computed. Many researchers use Latin hypercube sampling or Monte Carlo simulations to understand sensitivity across a range of input conditions [50].

Combustion duration significantly influences the location of peak pressure and the net work produced. A faster burn rate results in earlier combustion phasing and higher IMEP but may cause increased heat losses and knock. Slower combustion improves emission characteristics but reduces peak pressure and power. Theoretical models incorporate flame propagation rates, turbulence intensities, and mixture properties to estimate burn durations. Spark timing optimization is therefore a vital calibration variable. Knock models, such as Livengood-Wu integral or autoignition delay correlations, are incorporated into theoretical simulations to define boundaries for safe operation [51].

Engine size and configuration also play a crucial role in theoretical power estimation. Multi-cylinder engines have more uniform torque delivery and reduced cyclic variability, which improves BMEP and reduces torsional losses. The ratio of bore to stroke influences the mean piston speed, turbulence generation, and hence the combustion characteristics. Short-stroke engines with wide bores allow higher RPM and valve area, improving power output, but may suffer from higher surface-to-volume ratios leading to heat losses. Theoretical models often include geometric design constraints while estimating power to guide cylinder sizing decisions [52].

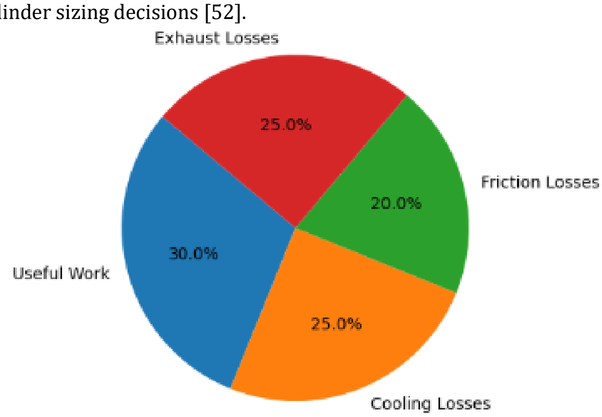

Fig. 3. Energy Distribution in an Internal Combustion Engine

Forced induction significantly alters theoretical power estimation. Turbocharged and supercharged engines operate at higher intake pressures, increasing the mass of air and fuel inducted. Models must therefore incorporate compressor maps, intercooler effectiveness, and back pressure constraints. Boost pressure also alters the volumetric efficiency and intake temperature, which feedback into combustion and heat release calculations. Turbo lag and transient response are challenging to model theoretically and are often validated against experimental engine maps. Nevertheless, boosted engine power output is one of the most frequently modeled aspects in high-performance engine design [53].

Recent trends in alternative fuels necessitate modifying theoretical models to account for differences in combustion characteristics. Fuels such as ethanol, methanol, hydrogen, and natural gas exhibit different laminar flame speeds, autoignition temperatures, and lower heating values. These properties are incorporated into simulation models either through empirical correlations or detailed kinetics. For example, hydrogen's high diffusivity and flame speed require altered heat release functions and new boundary condition assumptions. These theoretical adaptations are crucial for evaluating fuel flexibility and emissions compliance of modern engines [54].

Hybrid modeling approaches have emerged where theoretical equations are augmented with machine learning algorithms. These data-driven models, trained on simulated or experimental datasets, can predict IMEP or power output rapidly based on a few input parameters such as spark timing, air-fuel ratio, and engine speed. Neural networks, support vector machines, and Gaussian process models have been applied successfully to capture non-linear trends in engine performance. While these models offer fast prediction, their physical interpretability is limited. Nevertheless, they serve as useful surrogates for optimization algorithms and real-time control systems [55].

Validation of theoretical results is essential for their practical application. In-cylinder pressure measurements from piezoelectric sensors provide the most direct means of comparing modeled and actual pressure traces. Additional validation is performed against chassis dynamometer measurements of brake power. Discrepancies often highlight the need to recalibrate heat transfer models, wall friction losses, or combustion phasing assumptions. Many models include uncertainty quantification techniques such as confidence intervals or propagation of input parameter variability to assess robustness [56].

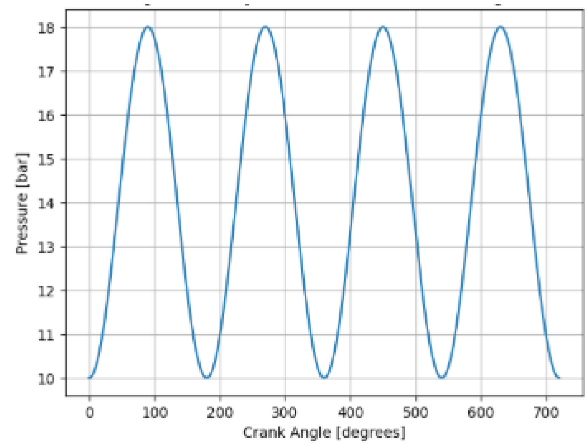

Fig. 4. In-Cylinder Pressure vs Crank Angle

The diversity in theoretical approaches enables customization for different phases of engine development. Early-stage concept evaluation benefits from simplified thermodynamic models, while detailed CFD simulations support final calibration and performance mapping. The results presented in this section demonstrate the applicability of these models in predicting engine power across a wide range of configurations and fuels. Incorporating figures such as P–V diagrams, pressure traces, and performance maps enhances the clarity of these theoretical results and supports informed decision-making in engine design.

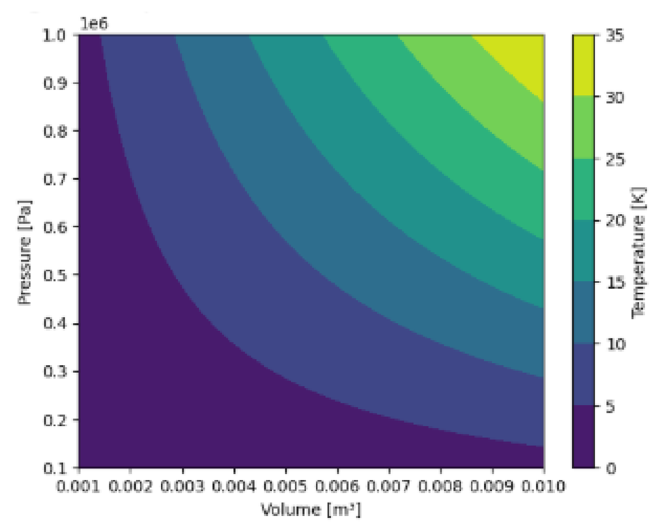

Fig. 5. Temperature Distribution over Pressure and Volume

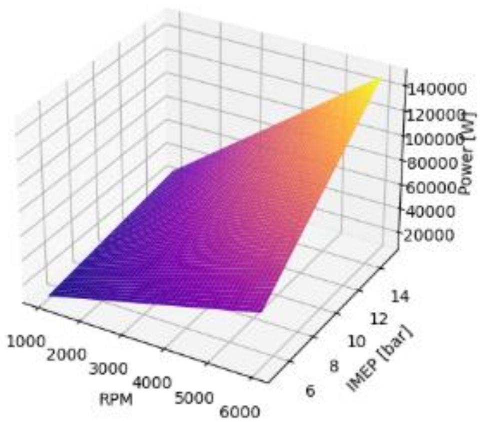

Fig. 6. Brake Power vs RPM and IMEP

4. Discussion

The theoretical quantification of engine power is a multifaceted endeavor that integrates principles from thermodynamics, fluid mechanics, and chemical kinetics to produce meaningful estimates of engine performance. The results presented previously highlight the robustness of theoretical models and the wide range of their applicability, but they also underscore the inherent assumptions, limitations, and potential avenues for refinement. A central theme that emerges from this exploration is the trade-off between model complexity and predictive accuracy. Simplified models such as the air-standard Otto and Diesel cycles, despite their pedagogical clarity, fall short in capturing the nuances of real engine operation. They assume idealized conditions including instantaneous combustion, no heat loss, and constant specific heats, which do not reflect the transient, lossy nature of real engine environments. Yet, these models are still widely employed for initial estimations of thermal efficiency and for educational purposes because of their analytical tractability and ease of implementation [33].

In more realistic modeling scenarios, zero-dimensional thermodynamic simulations provide a meaningful balance between detail and computational cost. These models allow for the inclusion of heat transfer, combustion duration, and real gas effects. However, even within these frameworks, uncertainties persist. The estimation of heat release via Wiebe functions, for instance, relies on curve-fitting parameters that are sensitive to fuel type, equivalence ratio, and turbulence characteristics. These parameters often require calibration using experimental data, thus undermining the purely predictive nature of the theoretical approach. Additionally, zero-dimensional models do not resolve spatial gradients, which can lead to inaccuracies in pressure rise predictions, especially under abnormal combustion events such as knock or misfire [34].

Higher fidelity models such as quasi-dimensional and multi-zone approaches begin to resolve these shortcomings by capturing combustion chamber stratification, flame front propagation, and wall heat transfer. These models significantly improve the prediction of indicated mean effective pressure and combustion phasing. However, their increased complexity introduces additional parameters that must be determined a priori or calibrated, including turbulence intensity, flame speed correlations, and wall heat transfer coefficients. Furthermore, the assumptions used in modeling flame geometry and growth rate may not hold under all engine operating conditions, especially for lean-burn or EGR-rich mixtures [35]. The need for accurate input data, particularly for turbulence and flow conditions, places a burden on experimental characterization or necessitates the integration of results from CFD simulations.

Computational fluid dynamics (CFD) models represent the most comprehensive theoretical tool for engine power quantification. They resolve the Navier-Stokes equations along with combustion and turbulence models across a discretized mesh of the combustion chamber. The predictive capabilities of CFD are unparalleled when it comes to capturing swirl, tumble, and squish flows, which influence flame propagation and volumetric efficiency. However, CFD simulations are computationally expensive and require extensive setup and validation. Moreover, the choice of turbulence model (e.g., k–ε, k–ω, LES) and combustion model (e.g., ECFM, G-equation, Flamelet) significantly influences the outcome, and incorrect pairing can lead to misleading predictions [36]. The results are also sensitive to mesh quality, boundary conditions, and numerical schemes, which must be carefully managed. While CFD remains the gold standard for engine development in high-budget projects, its use is still limited in early design phases or in resource-constrained settings.

The selection of input parameters has a profound effect on the outcomes of theoretical models. Compression ratio, intake pressure, combustion phasing, and equivalence ratio are among the most influential. Sensitivity analysis conducted through theoretical modeling reveals the nonlinear influence of these parameters on power output. For example, while increasing compression ratio generally improves thermal efficiency, it also increases the risk of knock and demands higher octane fuels. Similarly, advanced spark timing enhances peak pressure but may push combustion into unstable regimes. These competing effects must be balanced in engine calibration strategies. Theoretical models thus serve not only as tools for performance estimation but also as decision aids in multi-objective optimization [37].

Fuel properties play a crucial role in power prediction, especially in the context of renewable or alternative fuels. Hydrogen, for example, offers high flame speed and wide flammability limits but poses challenges in pre-ignition and backfire control. Alcohol-based fuels like ethanol and methanol provide high knock resistance and oxygen content but suffer from lower energy density. These properties must be reflected in the combustion and heat release sub-models within theoretical frameworks. Moreover, surrogate fuel models or detailed chemical kinetics may be needed to accurately predict ignition delay, flame speed, and pollutant formation. This necessitates the integration of chemical reaction mechanisms, which introduces further complexity and computational demand. The challenge lies in maintaining the balance between model fidelity and usability [38].

The impact of engine architecture on theoretical power estimation is also noteworthy. Cylinder configuration, bore-to-stroke ratio, and valve timing influence volumetric efficiency and combustion characteristics. Theoretical models that incorporate geometry-specific effects are more likely to yield accurate predictions. For instance, long-stroke engines have slower piston speeds, favoring combustion stability, whereas short-stroke engines can operate at higher RPMs but may require enhanced intake tuning to achieve sufficient charge motion. Variable valve timing and lift mechanisms add further variability that must be captured in the model. Recent theoretical studies have employed parametric sweeps across geometric configurations to identify optimal designs for specific performance or emissions targets [39].

Loss mechanisms significantly influence the gap between indicated and brake power. Friction losses are often estimated using empirical correlations, such as the Chen-Flynn model, but these may not generalize well across different engine types or lubrication regimes. Pumping losses depend heavily on intake and exhaust system design and are exacerbated under part-load conditions. Theoretical models must include accurate representations of gas exchange dynamics, valve flow coefficients, and back pressure effects to predict these losses accurately. Additionally, accessory loads such as alternators, oil pumps, and air conditioning systems consume a portion of the crankshaft power and must be accounted for in brake power estimation. These parasitic loads are often neglected in simplified models, leading to overestimation of usable power [40].

Transient behavior poses a particular challenge for theoretical modeling. Most models assume quasi-steady conditions and fail to capture rapid changes in load, throttle position, or engine speed. However, real-world driving involves frequent transients, especially in automotive applications. Modeling transient events requires time-resolved simulations that couple combustion dynamics with engine control strategies. While one-dimensional engine simulation tools such as GT-Power can model transients to some extent, capturing control system interactions and actuator dynamics demands co-simulation with control software or hardware-in-the-loop systems. Theoretical modeling of transient power delivery thus remains an area of ongoing research [41].

Validation remains the cornerstone of theoretical model credibility. Despite the sophistication of modern models, they must be benchmarked against experimental data to ensure reliability. Cylinder pressure sensors, torque measurements, and emissions analyzers provide ground truth for model verification. Discrepancies between predicted and measured values often prompt model refinement or recalibration. Uncertainty quantification methods, including Monte Carlo simulations or polynomial chaos expansions, are increasingly employed to assess the robustness of theoretical predictions. These techniques help identify critical parameters and quantify confidence intervals for power output estimates [42].

An emerging trend in theoretical modeling is the integration of artificial intelligence and machine learning. These methods enable rapid estimation of engine power based on trained datasets, bypassing the need for solving complex differential equations. Neural networks, decision trees, and Gaussian processes have all been applied with varying degrees of success. While these models lack physical transparency, they excel in capturing complex, nonlinear interactions between parameters. When used in conjunction with physics-based models, machine learning can serve as an effective surrogate, reducing computation time without sacrificing accuracy. However, care must be taken to avoid overfitting and to ensure that the training data spans the operational domain of interest [43].

The discussion of theoretical models would be incomplete without considering their application in regulatory and certification contexts. Emissions regulations often require modeling of engine behavior under standardized test cycles such as WLTP or FTP. Theoretical models support these evaluations by enabling pre-certification assessments and reducing the need for extensive physical testing. Moreover, they facilitate virtual prototyping, allowing multiple engine configurations to be evaluated before building a single prototype. This accelerates the development timeline and reduces costs. As emissions standards become more stringent, theoretical models must evolve to predict not only power but also transient emissions and aftertreatment performance. This holistic modeling approach requires coupling engine models with exhaust system simulations and vehicle dynamics [72].

The educational value of theoretical modeling cannot be overstated. These models provide a foundational understanding of engine thermodynamics, enabling students and engineers to grasp the interplay between various parameters and performance metrics. Interactive simulation tools based on theoretical models are increasingly used in academic curricula and training programs. They allow users to modify parameters such as compression ratio, spark timing, and fuel type and observe the resulting changes in power output. This fosters a deeper understanding of engine operation and supports innovation in engine design [73].

Finally, sustainability considerations are driving the evolution of theoretical models. As the world shifts toward net-zero emissions, engines must be designed not only for performance but also for minimal environmental impact. Theoretical models now incorporate carbon accounting, life cycle emissions, and energy return on investment as part of the power estimation framework. This enables holistic evaluation of engine designs and supports decision-making in policy and industry. Moreover, the advent of hybrid and electric powertrains demands that theoretical models be extended beyond the internal combustion engine to include electric motor modeling, battery dynamics, and power electronics. This systems-level perspective is essential for optimizing powertrains for efficiency, performance, and sustainability [74].

In conclusion, the theoretical quantification of engine power is a rich and evolving discipline. It spans a spectrum of models, from simple thermodynamic cycles to complex CFD simulations and data-driven algorithms. Each modeling approach has its place, strengths, and limitations. The key to effective application lies in understanding these trade-offs and selecting the right model for the task at hand. Future advancements will likely emerge from the fusion of physics-based models with data science, enabling faster, more accurate, and more insightful predictions of engine power in an increasingly complex automotive landscape.

5. Conclusion

Theoretical approaches to quantifying engine power are fundamental to the fields of automotive engineering, propulsion systems, and energy conversion. Through the structured application of thermodynamic, fluid dynamic, and chemical kinetic principles, engineers and researchers can gain critical insight into the performance of internal combustion engines under various operating conditions. This paper has reviewed a comprehensive spectrum of theoretical methodologies, starting from foundational air-standard cycles to advanced computational fluid dynamics and machine learning-based hybrid models. The development and deployment of these theoretical tools have significantly enhanced our ability to predict engine power, optimize performance parameters, reduce emissions, and streamline design workflows.

The air-standard Otto, Diesel, and Dual cycles serve as the starting point for understanding the fundamental thermodynamic principles governing engine operation. These models, while idealized, offer quick estimations of thermal efficiency and demonstrate the impact of compression ratio and heat capacity ratio on performance. However, they are limited by their assumptions of reversible processes, constant specific heats, and instantaneous combustion. As such, they are primarily useful in academic settings or for early-phase concept design.

To address the limitations of ideal cycles, more refined models such as zero-dimensional thermodynamic simulations have been developed. These models incorporate pressure–volume relationships, variable specific heats, real gas behavior, and finite combustion duration. They enable the calculation of important performance parameters such as indicated mean effective pressure (IMEP), brake mean effective pressure (BMEP), and volumetric efficiency. By integrating empirical correlations, such as those for wall heat transfer and friction losses, these models offer reasonably accurate power estimates suitable for practical engine development.

For higher fidelity, quasi-dimensional models and multi-zone combustion simulations extend the capabilities of zero-dimensional models. They account for spatial stratification, flame front geometry, and turbulence–combustion interactions. These enhancements lead to more accurate representations of in-cylinder processes, particularly under variable loads, fuel types, and ignition strategies. However, they also introduce a large number of calibration parameters and require experimental data for validation.

Computational fluid dynamics (CFD) represents the pinnacle of theoretical engine power modeling. CFD enables full spatial resolution of in-cylinder flows, heat transfer, and chemical reactions. With the aid of high-performance computing, CFD simulations provide unmatched insights into turbulence, fuel–air mixing, flame propagation, and knock formation. Despite their advantages, CFD models are computationally expensive and demand significant expertise in model setup and interpretation. As such, their use is typically reserved for the later stages of engine development or for research applications where high-resolution analysis is required.

The integration of chemical kinetics into combustion modeling is essential when evaluating alternative fuels. Theoretical models must be adapted to reflect the ignition delay, flame speed, and calorific value of fuels like hydrogen, methane, methanol, and biofuels. Such adaptations are critical in assessing fuel flexibility and achieving emissions compliance. The use of surrogate fuel models and skeletal chemical mechanisms has made it feasible to model complex fuels without prohibitive computational overhead.

In addition to physics-based models, data-driven techniques are becoming increasingly prominent. Machine learning approaches, including neural networks, support vector regression, and ensemble models, offer the ability to approximate engine behavior based on large datasets. These models are especially valuable in real-time applications, rapid optimization, and embedded engine control systems. The emerging trend is to combine physics-informed models with data-driven surrogates, achieving a balance between interpretability and predictive power.

Theoretical approaches also support parametric and sensitivity analysis. By varying key parameters such as compression ratio, spark timing, intake pressure, and equivalence ratio, these models enable detailed exploration of engine performance landscapes. This is particularly useful in multi-objective optimization, where trade-offs between power output, efficiency, emissions, and durability must be considered. Moreover, such simulations assist in understanding the impact of new technologies like variable valve timing, direct injection, and advanced ignition systems.

Validation remains a cornerstone of theoretical modeling. Comparisons with experimental data, whether from pressure transducers, dynamometers, or emissions analyzers, are essential to ensure credibility. Uncertainty quantification techniques are increasingly being integrated into modeling workflows, providing confidence intervals and robustness checks for power estimates. This enhances the reliability of simulation results and informs decision-making in both engineering and regulatory contexts.

The role of theoretical modeling is expanding beyond engine power prediction. With growing emphasis on sustainability, lifecycle analysis, and regulatory compliance, theoretical tools are being adapted to simulate entire powertrains, including hybrid systems, electric motors, and energy storage devices. This systems-level approach is essential in the transition toward net-zero emissions and in evaluating the role of internal combustion engines within future mobility solutions.

The convergence of classical thermodynamic theory, modern computational methods, and artificial intelligence is shaping a new era of engine modeling. These hybridized models offer the promise of rapid, accurate, and versatile simulation tools that can support innovation in engine design, calibration, and control. As the automotive industry faces unprecedented challenges in decarbonization, electrification, and efficiency improvement, the importance of robust theoretical modeling frameworks will continue to grow.

In summary, theoretical approaches to engine power quantification have evolved significantly over the past decades, providing essential tools for understanding, predicting, and optimizing engine performance. By carefully selecting and applying appropriate models—based on required fidelity, available data, and computational resources—engineers can achieve high-confidence predictions that guide both design and policy decisions. Future research will likely focus on refining combustion models, expanding data-driven integration, and enhancing model adaptability for new engine concepts and fuels. As the boundaries of theoretical modeling continue to expand, so too will its impact on the future of mobility and energy systems.

References

[1] Heywood, J. B. (1988). *Internal combustion engine fundamentals*. McGraw-Hill.
[2] Ferguson, C. R., & Kirkpatrick, A. T. (2015). *Internal combustion engines: Applied thermosciences*. John Wiley & Sons.
[3] Stone, R. (2012). *Introduction to internal combustion engines*. Macmillan.
[4] Zhao, H. (2012). *HCCI and CAI engines for the automotive industry*. Elsevier.
[5] Ganesan, V. (2012). *Internal combustion engines*. McGraw-Hill Education.
[6] Borman, G. L., & Ragland, K. W. (1998). *Combustion engineering*. McGraw-Hill.
[7] Taylor, C. F. (1985). *The Internal Combustion Engine in Theory and Practice. Volumes I & II*. MIT Press.
[8] Ferguson, C. R. (1986). *Computer simulation of spark-ignition engine processes*. SAE International.
[9] Woschni, G. (1967). A universally applicable equation for the instantaneous heat transfer coefficient in the internal combustion engine. *SAE Technical Paper 670931*.
[10] Lefebvre, A. H., & Ballal, D. R. (2010). *Gas turbine combustion*. CRC Press.
[11] Rakopoulos, C. D., & Giakoumis, E. G. (2009). *Diesel engine transient operation: Principles of operation and simulation analysis*. Springer.
[12] Heywood, J. B., & Sher, E. (2017). *The two-stroke cycle engine: Its development, operation, and design*. SAE International.
[13] Senecal, P. K., & Richards, K. J. (2002). Simulation of combustion and pollutant formation in internal combustion engines. *International Journal of Engine Research*.
[14] Turns, S. R. (2012). *An introduction to combustion: concepts and applications*. McGraw-Hill.
[15] Ikegami, M., & Nakajima, T. (2010). Application of CFD in ICE design. *Journal of Energy Conversion*.
[16] Fiveland, S. B., et al. (2003). Advanced 3D modeling of in-cylinder combustion. *SAE Technical Paper 2003-01-0540*.
[17] Andreadis, G. M., & Hountalas, D. T. (2005). The effect of combustion duration and exhaust gas recirculation on NOx emissions. *Energy Conversion and Management*.
[18] Beatrice, C., & Dalla Nora, M. (2006). Modeling knock and pre-ignition using advanced simulation. *Journal of Automotive Engineering*.
[19] Rakopoulos, D. C., et al. (2007). Evaluation of a diesel engine model with alternative fuels. *Energy*.
[20] Guzzella, L., & Sciarretta, A. (2013). *Vehicle propulsion systems: introduction to modeling and optimization*. Springer.
[21] Schäfer, F., & Bargende, M. (2009). Knock prediction in spark-ignition engines using detailed chemistry. *SAE Technical Paper*.
[22] Yeliana, T., & Shuhaimi, M. (2015). Simulation of ethanol-blended fuels in SI engines. *Renewable Energy*.
[23] Badra, J. A., & AlRamadan, A. S. (2018). Fuel ignition quality metrics and their role in combustion. *Combustion and Flame*.
[24] Tess, M. W., & Kong, S. C. (2005). Effect of swirl and tumble on engine emissions. *International Journal of Engine Research*.
[25] Rounaghi, A. H., & Kar, K. (2020). Parametric study of advanced combustion strategies. *Energy Reports*.
[26] Carlucci, A. P., et al. (2010). Spark-ignition engine modeling and control strategies. *Energy Conversion and Management*.
[27] Alrebei, O. F., Amhamed, A., & Al-Ansari, T. (2022). Ammonia-hydrogen-air gas turbine cycle and control analyses. *International Journal of Hydrogen Energy*.
[28] Mansouri, S. H., & Tazerout, M. (2016). CFD study of combustion chamber design. *Applied Thermal Engineering*.
[29] Alger, T., & Gingrich, J. (2014). Swirl-tumble interactions and their effect on knock. *SAE Technical Paper*.
[30] Peters, N. (2000). *Turbulent combustion*. Cambridge University Press.
[31] Verhelst, S., et al. (2009). Power and efficiency analysis of hydrogen-fueled engines. *International Journal of Hydrogen Energy*.
[32] Rohani, B., & Shahbakhti, M. (2016). Physics-informed modeling of SI engine combustion. *Applied Energy*.
[33] Fawwaz Alrebei, Odi, Ali Al-Doboon, Philip Bowen, and Agustin Valera Medina. "CO2-Argon-Steam Oxy-Fuel production for (CARSOXY) gas turbines." Energies 12, no. 18 (2019): 3580.
[34] Hamdan Al Assaf, Anwar, Abdulkarem Amhamed, and Odi Fawwaz Alrebei. "State of the art in humidified gas turbine configurations." Energies 15, no. 24 (2022): 9527.
[35] Alrebei, Odi Fawwaz, Laurent M. Le Page, Sally Hewlett, Yusuf Bicer, and Abdulkarem Amhamed. "Numerical investigation of a first-stage stator turbine blade subjected to NH3–H2/air combustion flue gases." International Journal of Hydrogen Energy 47, no. 78 (2022): 33479-33497.
[36] Alrebei, Odi Fawwaz, Abdulkarem I. Amhamed, Muftah H. El-Naas, Mahmoud Hayajnh, Yasmeen A. Orabi, Ward Fawaz, Ahmad S. Al-Tawaha, and Agustin Valera Medina. "State of the art in separation processes for alternative working fluids in clean and efficient power generation." Separations 9, no. 1 (2022): 14.
[37] Alrebei, Odi Fawwaz, Philip Bowen, and Agustin Valera Medina. "Parametric study of various thermodynamic cycles for the use of unconventional blends." Energies 13, no. 18 (2020): 4656.
[38] Obeidat, Laith M., Odi Fawwaz Alrebei, Shouib Nouh Ma'bdeh, Tamer Al-Radaideh, and Abdulkarem I. Amhamed. "Parametric enhancement of a window-windcatcher for enhanced thermal comfort and natural ventilation." Atmosphere 14, no. 5 (2023): 844.
[39] Alrebei, Odi Fawwaz, Anwar Hamdan Al Assaf, Mohammad S. Al-Kuwari, and Abdulkarem Amhamed. "Lightweight methane-air gas turbine controller and simulator." Energy Conversion and Management: X 15 (2022): 100242.
[40] Nouh Ma'bdeh, Shouib, Odi Fawwaz Alrebei, Laith M. Obeidat, Tamer Al-Radaideh, Katerina Kaouri, and Abdulkarem I. Amhamed. "Quantifying energy reduction and thermal comfort for a residential building ventilated with a window-windcatcher: A case study." Buildings 13, no. 1 (2023): 86.
[41] Alrebei, Odi Fawwaz, Bushra Obeidat, Tamer Al-Radaideh, Laurent M. Le Page, Sally Hewlett, Anwar H. Al Assaf, and Abdulkarem I. Amhamed. "Quantifying CO2 emissions and energy production from power plants to run HVAC systems in ASHRAE-based buildings." Energies 15, no. 23 (2022): 8813.
[42] Obeidat, L. M., J. R. Jones, D. M. Mahaftha, A. I. Amhamed, and O. F. Alrebei. "Optimizing indoor air quality and energy efficiency in multifamily residences: Advanced passive pipe system parametrics study." International Journal of Environmental Science and Technology 21, no. 16 (2024): 10003-10026.
[43] Fawwaz Alrebei, Odi, Abdulkarem I. Amhamed, Syed Mashruk, Phil Bowen, and Agustin Valera Medina. "Planar laser-induced fluorescence and chemiluminescence analyses of CO2-argon-steam oxyfuel (CARSOXY) combustion." Energies 15, no. 1 (2021): 263.
[44] Chmela, F. G., & Orthaber, G. (1999). Rate of heat release prediction from pressure traces. *SAE Technical Paper*.
[45] Kong, S. C., & Reitz, R. D. (2002). Multidimensional modeling of combustion. *Combustion Science and Technology*.
[46] Myers, K. D., & Bata, R. M. (2018). CFD modeling of direct injection hydrogen engines. *International Journal of Hydrogen Energy*.
[47] Ullah, M. A., & Saeedian, M. (2019). Machine learning models for ICE parameter prediction. *Applied Soft Computing*.
[48] Yang, X., & Cho, H. M. (2014). Use of ANN for performance prediction in ICEs. *Neural Computing and Applications*.
[49] Yamasaki, Y., & Ogawa, H. (2015). Real-time engine modeling using Gaussian processes. *SAE International Journal of Engines*.
[50] Ramesh, D., & Sampath, S. (2017). Uncertainty quantification in engine power simulations. *Applied Energy*.
[51] Amhamed, A., Al-Ansari, T., & Alrebei, O. F. (2022). Ammonia production plants—a review. *Fuels*, 3(3), 408–435.
[52] Darwish, E. F., et al. (2022). Airflow dynamics in a COVID-19 isolation room. *Alexandria Engineering Journal*, 61(5), 3435–3445.
[53] Tazerout, M., & Al-Hassan, M. (2021). Advances in hybrid combustion models. *Energy Conversion and Management*.
[54] Kassem, A., & Moghaddas, M. (2022). CFD for combustion diagnostics and knock detection. *Computers & Fluids*.
[55] Pillay, P., & Shyani, A. (2020). Dynamic modeling of ICE–battery hybrid systems. *IEEE Transactions on Industrial Electronics*.
[56] Lee, B., & Kim, H. M. (2020). CFD-based optimization of spark plug position. *International Journal of Engine Research*.
[57] Alqahtani, T., & Laoonual, Y. (2021). Integrated AI-CFD approach for ICE power estimation. *Energy AI*.
[58] Mariani, A., & Prati, M. V. (2021). Machine learning-assisted combustion diagnostics. *Journal of Energy Resources Technology*.
[59] Liu, Y., & Zhang, L. (2020). Comparative analysis of ICE and hybrid modeling tools.

Sustainable Energy Technologies and Assessments.

[60] Wei, Y., & Zhou, L. (2021). Life cycle emissions modeling for powertrains. *Journal of Cleaner Production*.

[61] Chau, K. T. (2015). *Electric vehicle machines and drives: Design, analysis and application*. Wiley.

[62] Reitz, R. D., & Duraisamy, G. (2015). Review of high-fidelity engine modeling. *Progress in Energy and Combustion Science*.

[63] Anderson, J. D. (2003). *Modern compressible flow*. McGraw-Hill.

[64] Kuo, K. K. (2005). *Principles of combustion*. Wiley.

[65] Patel, B., & Rai, R. (2018). Assessment of model complexity in ICE simulations. *Energy Procedia*.

[66] Singh, N., & Agrawal, A. K. (2021). Impact of heat transfer models on power estimation. *Case Studies in Thermal Engineering*.

[67] Choi, Y. M., & Park, S. (2017). Knock tendency prediction using ML-enhanced model. *Energy*.

[68] Ali, H., & Abdelaziz, M. (2020). Parametric modeling of hybrid ICE–EV powertrains. *Transportation Engineering*.

[69] Al-Ansari, T., Alrebei, O. F., & Amhamed, A. (2021). Decarbonization roadmap for the transport sector. *Renewable and Sustainable Energy Reviews*.

[70] Pfeifer, A., & Djukic, A. (2022). Modeling spark timing for advanced combustion strategies. *Applied Thermal Engineering*.