Article citation info:
Jakubowski R, Szumski M. Application of ChatGPT in the generation of a numerical performance model of a turbofan engine. Combustion Engines. 0000;XXX(X):xx-xx. https://doi.org/10.19206/CE-213555

Robert JAKUBOWSKI
Marek SZUMSKI

Combustion Engines
Polish Scientific Society of Combustion Engines

Application of ChatGPT in the generation of a numerical performance model of a turbofan engine

ARTICLE INFO

Received: 16 May 2025
Revised: 13 October 2025
Accepted: 23 October 2025
Available online: 15 January 2026

This paper presents a study on the application of ChatGPT 4.0 in developing a numerical model for the performance analysis of a turbofan engine. The modeling process began with general queries regarding numerical approaches to engine simulation. The initial model proposed by ChatGPT appeared plausible but contained significant conceptual errors. Through iterative dialogue and refinement, these errors were gradually identified and corrected, ultimately resulting in a valid engine model. This intermediate model included two rotating components (fan and core spool) and assumed an ideal gas with distinct thermodynamic properties in the cold and hot sections of the engine. Based on this model, ChatGPT successfully generated numerical code for implementation in the MATLAB environment, handling this task with high accuracy and flexibility. Further efforts focused on extending the model to include air extraction for turbine cooling, internal engine bleeds, and the application of a semi-perfect gas model to describe the working fluid more realistically. In these more advanced areas, ChatGPT's performance declined significantly. Despite prompting and corrective guidance, it was unable to produce a fully functional and physically accurate implementation of the enhanced model. The study concludes that while ChatGPT demonstrates strong capabilities in translating well-defined physical models into numerical code, especially within MATLAB, it remains unreliable in constructing or modifying complex thermodynamic models without significant user oversight. Nonetheless, its use can significantly accelerate the implementation phase of numerical engine modeling when guided by an experienced user.

Key words: *turbofan engine modeling, ChatGPT in engineering, artificial intelligence applications, gas turbine performance analysis*

1. Introduction

The generation of accurate, reliable, and above all problem-adequate models constitutes a critical issue in both engineering practice and scientific research. A substantial body of literature is dedicated to the challenges of modeling technical systems as well as to the tools and methodologies employed in this context. This aspect is particularly prominent in aerospace engineering, where model-based investigations play a vital role not only in testing and optimizing existing designs but also in supporting the development of new concepts and their optimisation [35].

The full spectrum of modeling challenges in the field of aeronautics is highly complex due to the vast scope of the subject. The present study focuses on modeling the propulsion system, which is itself a highly complex technical system that requires a multidimensional analytical approach. Consequently, depending on the specific research objectives, engine modeling can be addressed from various perspectives, taking into account both the intended purpose of the study and the required level of model fidelity [23]. Research involving numerical modeling addresses a range of issues, including engine performance, as demonstrated in studies [2, 5, 11, 20, 35]; environmental impact, such as pollutant and greenhouse gas emissions [14, 16–18, 27]; structural integrity assessments [12]; and flow analysis within the engine or its selected components [1, 25, 31, 33]. In many cases, these issues are interrelated, with the results of one type of analysis serving as input data for subsequent analyses. For instance, in [1], the results of gas-dynamic parameter calculations in the engine control stations are used as boundary conditions for flow analysis in the compressor rotor, and the outcomes of this analysis are subsequently applied in evaluating engine performance. Similarly, in [16], engine operating parameters obtained from performance calculations are used as input for emissions modeling, while in [12], flow simulations form the basis for the structural analysis of the compressor. Consequently, there is a growing trend toward integrating models operating in different computational domains to improve the efficiency of data exchange between them. This facilitates the development of computational systems that are increasingly becoming complex, multidisciplinary tools.

Steady-state analyses are not always sufficient; in many cases, it is necessary to investigate unsteady phenomena – not only in scenarios involving changes in engine operating conditions, such as acceleration or deceleration, but also under steady-state operation to assess interactions between rotating and stationary components of the engine [31, 33], where unsteady effects are also analyzed. However, such detailed modeling requires significant computational resources and time for model setup and execution, resulting in high research costs. In many cases, a significantly more cost-effective approach is used, involving a variation in the level of model fidelity across engine components – known as the multifidelity approach – as demonstrated in studies [1, 5, 25]. In this method, a selected engine module, such as the compressor flow path [5, 25], is modeled in detail using a more complex model, while other components are represented using simplified methods. This approach enables a substantial reduction in computational time and cost while maintaining high accuracy within the targeted area of investigation.

Engine performance calculations are still predominantly based on quasi-one-dimensional (pseudo-1D) analysis, which relies on averaged thermodynamic parameters of the flow in the engine's control stations. This approach is represented in studies such as [2, 4, 9–11, 21–23], where flow parameters are determined in selected control sections to evaluate engine performance. The modeling is grounded in the conservation equations of mass, momentum, and energy. At the same time, the processes occurring in individual engine components are characterized using efficiency parameters that account for deviations from idealized, reversible transformations.

A similar approach is employed by dedicated computational tools, such as the GasTurb Program, Gas Turbine Simulation Program (GSP), and the Propulsion Object-Oriented Simulation Software (PROOSIS) [2], which are advanced tools for analyzing the performance of gas turbine engines. Their additional computational modules also enable the determination of other operating parameters of a jet engine, as demonstrated in [14], where the GasTurb software was used to calculate NO_x emissions for the F100-PW-229 engine.

In [2], it was noted that the use of commercial tools requires access to the licenses, which could be expensive. Moreover, users frequently lack access to the program's source code, which prevents them from adapting it to meet the needs of their research, thereby reducing the researcher's role to that of an operator rather than a developer. For this reason, proprietary in-house programs for aero engine performance calculations continue to be developed, based on the laws of physics and chemistry and tailored to specific computational requirements, as demonstrated in studies such as [2, 9–12, 21]. Additionally, the development of numerical methods enables their adaptation for creating new tools in the field of aircraft engine model preparation. For example, in [29], fuzzy logic was employed to develop an engine model, whereas in [19], neural networks were used to construct a compressor map model for engine performance analysis.

In recent years, emerging and rapidly advancing artificial intelligence (AI) technologies have opened up new possibilities for model development and analytical research. Recent advancements in AI, particularly the emergence of Large Language Models (LLMs), have opened new avenues for supporting engineering design and computational tasks [29, 30]. Various tools based on LLMs are currently being developed by companies such as Google, Microsoft, and others. One of the most widely recognized examples is ChatGPT. ChatGPT, in particular, has been explored as a tool for assisting in code development, algorithm generation, and even conceptual design ideation, with early results indicating both its versatility and limitations [6, 28].

Recent studies have shown that LLMs can assist in conceptual design, requirement generation, and early-phase engineering workflows [15]. They facilitate the automation of repetitive tasks, offer support in code generation and debugging, and contribute to technical documentation with high efficiency [28]. Domain-specific tuning, as seen in AviationGPT, further enhances its applicability to specialized tasks, including aviation safety reports and aircraft systems analysis [34].

LLMs are also being considered as collaborative agents in engineering design processes. When used within structured frameworks, they support ideation, generate architectural proposals, and facilitate cross-domain communication [29, 30, 32]. Their ability to process large volumes of data and produce meaningful summaries or insights makes them particularly useful in system-level engineering tasks.

In the context of aviation, artificial intelligence tools, including LLMs, are viewed as key enablers of next-generation operations and training. Their integration is linked to changes in the required skillsets for aviation professionals, with an increasing emphasis on AI literacy and human-machine collaboration [13].

Despite their strengths, the studies also highlight significant limitations. LLMs often produce outputs that are syntactically correct but semantically flawed or factually inaccurate [28, 32]. They may hallucinate technical content, misinterpret standards, or apply inconsistent logic in complex engineering tasks. These risks are particularly critical in safety-sensitive fields, such as aerospace.

Furthermore, performance across different LLM frameworks varies considerably. Their effectiveness in handling highly specific or quantitative engineering tasks remains limited unless paired with dedicated tools or domain-specific training [30]. Human validation and oversight are still essential to ensure correctness and reliability.

This paper examines the practical application of ChatGPT 4.0 in developing a numerical performance model for a turbofan engine. The study employed the free version of ChatGPT, a widely accessible tool used by a broad community of users. The primary objective was to utilize this tool to assist in developing a turbofan engine performance model, which would then be translated into executable code within a selected computing environment – in this case, MATLAB. The aim was to assess the level of model complexity that could be achieved through such an approach, as well as to evaluate the correctness of the resulting model. In doing so, we sought to determine whether a user without prior expertise in this specific domain could generate a valid computational model, potentially applicable to broader tasks such as aircraft performance analysis or numerical simulation-based testing.

2. ChatGPT utilization for turbofan engine calculation

This study investigates whether ChatGPT 4.0, available in its free version at the beginning of 2025, is capable of generating a turbofan engine performance model. The focus is on evaluating the model initially proposed by the tool and assessing how well it aligns with standard methods commonly used for such analyses. The generated results are systematically validated using established and verified computational tools previously developed for this purpose.

In cases where inconsistencies or errors are identified, an iterative dialogue is conducted with the language model to address and correct the issues. All modifications are directly implemented into the computational code and continuously validated against the reference model.

Once a correct elementary performance model is established, further work will focus on its expansion to include elements of more advanced models–for example, incorporating compressor bleed flows, turbine cooling flows, and working fluid properties modeled using semi-perfect gas formulations. The overall workflow is illustrated in the schematic diagram presented in Fig. 1.

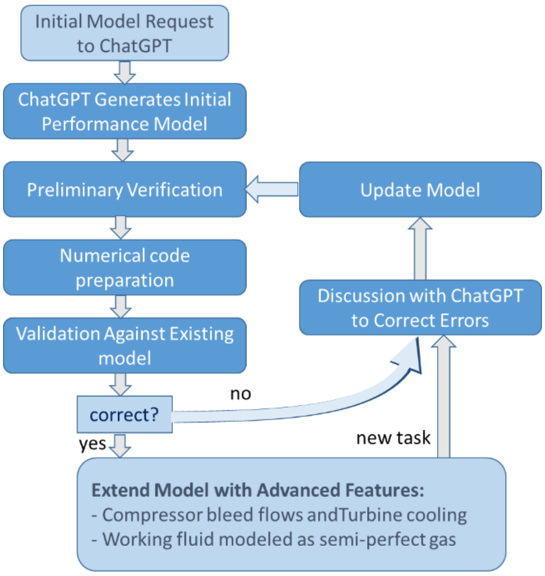

Fig. 1. Workflow for turbofan engine model development using ChatGPT

2.1. Turbofan engine model

In the first stage, ChatGPT was asked to develop a numerical model for calculating the performance of a turbofan engine. The instruction was formulated as follows:

"*Could you provide the algorithm for turbofan engine thrust (F) and specific fuel consumption (SFC) calculation for defined bypass ratio (BPR) fan pressure ratio (FPR), compressor pressure ratio (CPR), turbine Inlet Temperature (TIT) mass flow rate. Engine model should include pressure losses and rotating part efficiencies*".

The GPT response provided a computational algorithm that was structured with a clear specification of input data and a numerical model. Input data included fundamental engine parameters such as bypass ratio (BPR), fan pressure ratio (FPR), compressor pressure ratio CPR, turbine inlet temperature TIT, and engine mass flow rate m_{total}. Next, parameters characterizing component efficiencies and flow pressure losses were specified. Finally, the input data included ambient conditions, such as air temperature T0 and pressure P0, as well as gas properties, including specific heat capacity, isentropic exponent, and individual gas constants.

A complete computational model of the engine generated by ChatGPT is presented in Fig. 2. It is worth noting that the overall structure of the model was reasonably well-prepared and logically organized, enabling the calculation of the specified parameters: engine thrust (F) and specific fuel consumption (SFC). However, several errors were present in the model, which could have affected the accuracy of the calculations. Incorrect or insufficiently precise formulas are summarized in Table 1.

The formulas presented in Table 1 appear similar to the correct ones but contain errors that would lead to discrepancies between the obtained results and the models found in the literature [4, 8, 23] cited by ChatGPT as the source for developing the algorithm. Additionally, the specific thrust was defined only in relation to the mass flow rate in the core flow $ST = T/m_{core}$, and in the generated equation for specific fuel consumption, the fuel mass flow parameter was used, despite not being determined in the model. Furthermore, the section following the fan, which is conventionally referred to as station 13 in bypass flow and 23 in core flow, is labeled as station 2 in the algorithm prepared by ChatGPT.

Step-by Step Calculations

1. Fan and Bypass Steram:

- Fan exit pressure and temperature:

$$P_2 = P_0 \ \mathrm{FPR}$$

$$T_2 = T_0\left(1 + \frac{\eta_f}{\eta_c}\left(\mathrm{FPR}^{(\gamma-1)/\gamma} - 1\right)\right)$$

- Bypass flow exit conditions (assuming isentropic expansion in bypass nozzle):

$$P_{\text{bypass exit}} = P_2 \ \pi_{\text{bypass}}$$

$$T_{\text{bypass exit}} = T_{\text{bypass}}$$

- Velocity of bypass stream

$$V_{\text{bypass}} = \sqrt{2\,\eta_n c_p\left(T_{\text{bypass exit}} - T_0\right)}$$

2. Core engine (Compressor Combustor and Turbine)

- Compressor exit conditions:

$$P_3 = P_2 \ \mathrm{CPR}$$

$$T_3 = T_2\left(1 + \frac{\eta_c}{\eta_f}\left(\mathrm{CPR}^{(\gamma-1)/\gamma} - 1\right)\right)$$

- Turbine exit conditions:
  - Available enthalpy drop across turbine:

$$\Delta h_t = c_p(T_4 - T_3)$$

  - Turbine exit temperature:

$$T_5 = T_4 - \frac{\Delta h_t}{\eta_t}$$

  - Turbine exit pressure

$$P_5 = P_3 \ \pi_b \left(\frac{T_5}{T_4}\right)^{\gamma/(\gamma-1)}$$

- Velocity of core exhaust

$$V_{core} = \sqrt{2\,\eta_n c_p(T_5 - T_0)}$$

3. Thrust Calculation

The total thrust is the sum of the momentum flux from the bypass and core stream

$$F = \dot{m}_{bypass} V_{bypass} + \dot{m}_{core} V_{core} - \dot{m}_{total} V_0$$

where V_0 is the freestream velocity

4. Fuel Flow and Specific Thrust

- Fuel-to-air ratio (FAR):

$$\mathrm{FAR} = \frac{c_p(T_4 - T_3)}{\eta_b \ \mathrm{LHV}}$$

- Sopecific Thrust:

$$\mathrm{ST} = \frac{F}{\dot{m}_{core}}$$

- Specific Fuel Consumption (SFC):

$$\mathrm{SFC} = \frac{\dot{m}_{fuel}}{F}$$

Fig. 2. Turbofan engine model generated by ChatGPT

Table 1. Incorrect or insufficiently precise formulas generated by Chat GPT

Parameter	Formula given by ChatGPT	Correct formula [8]
Fan exit temperature	$T_2 = T_0\left(1 + \frac{\eta_f}{\eta_c}\left(FPR^{(\gamma-1)/\gamma} - 1\right)\right)$	$T_2 = T_0\left(1 + \frac{1}{\eta_f}\left(FPR^{(\gamma-1)/\gamma} - 1\right)\right)$
Compressor exit temperature	$T_3 = T_2\left(1 + \frac{\eta_c}{\eta_f}\left(CPR^{(\gamma-1)/\gamma} - 1\right)\right)$	$T_2 = T_0\left(1 + \frac{1}{\eta_c}\left(CPR^{(\gamma-1)/\gamma} - 1\right)\right)$
Turbine enthalpy drop	$\Delta h_t = c_p(T_4 - T_3)$	$\Delta h_t = c_p(T_4 - T_5)$
Turbine exit temperature	$T_5 = T_4 - \frac{\Delta h_t}{\eta_t}$	$T_5 = T_4 - \Delta h_t$
Turbine exit pressure	$P_5 = P_3\pi_b\left(\frac{T_5}{T_4}\right)^{\gamma/(\gamma-1)}$	$P_5 = P_3\pi_b\left(1 - \frac{1 - T_{t5}/T_{t4}}{\eta_T}\right)^{\frac{\gamma}{\gamma-1}}$
Velocity of core exhaust	$V_{core} = \sqrt{2\eta_n c_p(T_5 - T_0)}$	$V_{core} = \sqrt{2\eta_{n\,core} c_p(T_5 - T_{5\,st})}$
Velocity of bypass stream	$V_{bypass} = \sqrt{2\eta_n c_p\left(T_{bypass\_ex} - T_0\right)}$	$V_{bypass} = \sqrt{2\eta_{n\,bypass} c_p} * \sqrt{T_{bypass} - T_{bypas\,st}}$

2.2. Engine computational algorithm in Matlab

ChatGPT was asked to generate an algorithm suitable for execution in the Matlab environment. The algorithm was prepared as a Matlab function, where the engine thrust and specific fuel consumption were generated as output data, while the input data included the fundamental parameters of the turbofan engine and efficiencies of its components. Additionally, ChatGPT suggested input data for the calculations, as presented below, and described the calculation initialization process as shown below:

```
BPR = 6;          % Bypass ratio [–]
FPR = 1.6;        % Fan pressure ratio [–]
CPR = 30;         % Compressor pressure ratio [–]
TIT = 1400;       % Turbine inlet temperature [K]
m_core = 20;      % Core mass flow rate [kg/s]
eta_f = 0.9;      % Fan efficiency [–]
eta_c = 0.88;     % Compressor efficiency [–]
eta_t = 0.9;      % Turbine efficiency [–]
eta_n = 0.98;     % Nozzle efficiency [–]
pi_b = 0.95;      % Burner pressure loss factor [–]
pi_bp = 0.98;     % Bypass pressure loss factor [–]
T0 = 288;         % Ambient temperature [K]
P0 = 101325;      % Ambient pressure [Pa]

[F, SFC] = turbofan_calc(BPR, FPR, CPR, TIT, m_core, eta_f, eta_c, eta_t, eta_n, pi_b, pi_bp, T0, P0);
```

The proposed data appear reasonable for calculations of an engine from the 1980s–1990s, as noted in [23]. They correspond to operating conditions at zero flight speed under ISA conditions. To adapt these data to the CFM-56-2 present-day engine [3], some parameters proposed by ChatGPT were modified as follows:

```
FPR = 1.45;       % Fan pressure ratio [–]
CPR = 20;         % Compressor pressure ratio [–]
m_core = 52;      % Core mass flow rate [kg/s]
TIT = 1600;       % Turbine inlet temperature [K]
```

The structure of the proposed computational algorithm was also thoroughly analyzed. In the algorithm, unlike the model presented in Fig. 2, the equations for the temperature behind the fan and compressor were correctly formulated. Additionally, the enthalpy drop across the turbine was properly defined as the temperature drop between sections 4 and 5. This was determined based on the energy demand of the fan and compressor, which is a correct approach that was not included in the presented model. For the pressure calculations behind the turbine, the algorithm, like the model, used the isentropic expansion relationship (without losses).

However, some errors were identified in the prepared algorithm. One issue was the fuel consumption calculation, which, although based on a fairly well-written equation, incorrectly used the turbine efficiency instead of the combustion chamber thermal efficiency. Furthermore, incorrect equations for the exhaust gas velocity were repeated for both engine nozzles. The formula for calculating engine thrust was also incorrectly formulated as follows:

$$F = \left(m_{bypass}V_{bypass} + m_{core}V_{core}\right) - m_{total}\sqrt{\gamma R_{air} T_0} \quad (1)$$

The equation (1) includes an incorrect expression for the engine's velocity speed of sound formula $\sqrt{\gamma R_{air} T_0}$ instead of flight speed.

To summarize this section, it is worth noting that ChatGPT developed a plausible turbofan engine model. It includes almost all the required elements characterizing the performance of this type of engine. However, in many cases, errors appear in the provided equations, which will undoubtedly affect the accuracy of the calculations. ChatGPT also developed a function for calculations in the Matlab program. In the developed code, some errors present in the model were eliminated, even though the issue was never discussed. Nevertheless, the resulting computational algorithm still contains formulas that will lead to errors in the obtained calculation data.

2.3. Comparison of engine calculation results

Based on the works [2, 7, 9, 23] a turbofan engine model in Matlab was prepared, which was called "Correct model". This model was used to validate the calculation results from the models prepared by ChatGPT. The data proposed by ChatGPT after mentioned modification was used, supplemented with missing information, such as the combustion chamber efficiency, which was assumed to be 98%, and calculations were performed. The results are summarized in Table 2, along with a comparison to the available data for the CFM-56 engine. The first three parameters

(BPR, m_{total}, OPR) were assumed parameters represent the input data assumed at the same level in the calculations using both models. They are from the range of data given for this engine in [3].

Table 2. Comparison of results from the ChatGPT-developed model, the correct model, and the data for the CFM-56 engine [3]

Parameter	ChatGPT	Correct model	CFM-56-2 data
BPR [–]	6	6	5.9–6
m_{total} [kg/s]	364	364	356–31
OPR [–]	31.9	31.9	30.5–31.8
Takeoff thrust [kN]	13.4	100.6	96–106.7
TSFC [g/(kNs)]	85.26	10.7	10.4–10.7

The ChatGPT algorithm calculation results show significant discrepancies compared to the correct engine model. The calculation errors are at an unacceptable level. The computed takeoff thrust is approximately 8 times lower, and the TSFC is more than 8 times higher than what the correct model should produce.

2.4. Improvement of the model through discussion with ChatGPT

Based on the analysis of errors found in the model, a discussion with ChatGPT was initiated to eliminate them. The discussion started by pointing out that the exhaust gas velocities from both nozzles were being calculated incorrectly. ChatGPT was asked to correct the exhaust gas velocity equations, considering full expansion in the nozzle. The correction provided by ChatGPT was accurate.

The next comment concerned the flight velocity equation used in the calculation of engine thrust. ChatGPT was asked to correct it by introducing the Mach number as an additional variable to determine the flight velocity. Additionally, it was asked to include the dynamic compression at the engine inlet (ram effect) in the calculations of temperature and pressure before the fan. These suggestions were correctly implemented in the engine model.

In the next steps, ChatGPT was asked to consider that the turbine is not ideal and undergoes a non-isentropic process by incorporating the isentropic efficiency in the formula for the pressure behind the turbine. Next was pointed out that for the combustion chamber, the thermal efficiency of the combustion chamber should be used instead of the turbine efficiency. Additionally, it was specified that the flow losses in the bypass duct should be considered in the calculation of the pressure in the external nozzle. Finally, the value of specific heat for the flow in the hot section of the engine was modified to align with typical values used in literature [4, 23].

After implementing all these corrections into the model, ChatGPT was asked to regenerate the function in the Matlab environment. The modified function was used to perform calculations for the previously used CFM-56 engine data set. The calculation results are presented in Table 3. This time, the data shows a sufficient level of agreement with the engine's reference data (see Table 2). The thrust falls within the range of values reported for this engine, and the specific fuel consumption is only slightly below the minimum value. This would require only minor adjustments to the model to achieve results within the expected range.

Table 3. Results from the ChatGPT-corrected model

Parameter	ChatGPT corrected model
Takeoff thrust [kN]	103.8
TSFC [g/(kNs)]	10.1

2.5. Expanding the engine model using ChatGPT

The initially prepared and improved model from ChatGPT underwent further modifications better to align it with the design of the analyzed engine. The modifications were also aimed at using complex computational models of the gas flowing in the engine. The modifications were implemented in stages by sending targeted queries to the system.

Two spool engine model

The first step was to separate the engine calculations into two rotors, as the previously obtained model treated the fan and compressor assembly as a single unit.

To achieve this, the following command was executed: "*Separate the computational model for the fan and compressor assembly into two rotors, assuming that the low-pressure rotor consists of a fan characterized by the Fan Pressure Ratio (FPR) and fan efficiency, as well as a low-pressure compressor defined by the Low-Pressure Compressor Pressure Ratio (LPCPR) and compressor efficiency. The high-pressure assembly consists of a high-pressure compressor with a specified High-Pressure Compressor Pressure Ratio (HPCPR) and efficiency. Both compressors are located in the engine's inner bypass duct*"

This generated a breakdown of the engine compression in the model into three separate modules, but the turbine was still calculated as a single unit. Therefore, the next prompt was to ensure that separate turbines for the high and low-pressure spools were included in the model. After executing this command, a model was created, but the load between the turbines was incorrectly distributed. The load on the high-pressure turbine was defined by the temperature change in the combustion chamber, while the entire power demand for the compressors and fan was assigned to the low-pressure turbine.

This issue was presented to ChatGPT, and it was then asked to correct the problem. Unfortunately, its modifications further degraded the model. It removed turbine efficiency from the pressure calculations and instead applied it to the enthalpy change calculations. At this point, it became necessary to explicitly specify the exact changes that ChatGPT needed to implement to fix the model.

The discussion with ChatGPT regarding the introduction of mechanical efficiency into the model for calculating the balance between the high-pressure turbine and high-pressure compressor, and the low-pressure turbine and low-pressure compressor, plus fan, failed. ChatGPT made changes to the model that did not align with the instructions provided, continuously treating the turbine efficiencies as mechanical efficiencies.

To fix the algorithm, it was necessary to specify explicitly how the calculation of the turbine-compressor balance should be modified, providing the exact equations to be incorporated. This allowed for the correction of the computational algorithm, accurately representing the operation of a two-shaft engine model.

HPT cooling

The next instruction concerned implementing bleed flows in the engine for turbine cooling, assuming that the entire cooling flow is supplied to the high-pressure turbine and then returns to the main flow.

A prompt was used in the form of: *"Please correct this model to account for a bleed flow of 8% of the core mass flow after the high-pressure compressor. Direct this flow to the high-pressure turbine for cooling. Incorporate the applied cooling into the turbine's work balance and adjust the combustion chamber calculations to reflect the change in mass flow due to this bleed.*"

High-Pressure Turbine (HPT) Power Calculation with Cooling

Given:

Bleed flow fraction: $\dot{m}_{bleed} = \beta\,\dot{m}_{core}$, where $\beta = 0.08$ (8%)

Corrected mass flow into the combustor:

$$\dot{m}_{comb} = \dot{m}_{core}\,(1-\beta)$$

Total mass flow throught the HPT (includig cooling air):

$$\dot{m}_{HPT} = \dot{m}_{comb} + \dot{m}_{bleed} = m_{core}$$

Since the cooling flow is eventually reintroduced into the turbine stream, the total work extracted by the high-pressure turbine remains the same, but the enthalpy drop calculation must reflect the mixed flow

Power Balance for HPT

The high-pressure extracts power to drive the high-pressure compressor (HPC), considering mechanical transmission losses:

$$W_{HPT} = \frac{W_{HPC}}{\eta_{mech,HPT}}$$

where

$$W_{HPC} = \dot{m}_{comb}\,c_{p,cold}\,(T_3 - T_{25})$$

Thus, the corrected enthalpy drop in the HPT is:

$$h_{HPT} = \frac{c_{p,cold}\,(T_3 - T_{25})}{\eta_{mech,HPT}}$$

The exit temperature of the HPT is

$$T_{45} = T_4 - \frac{h_{HPT}}{c_{p,hot}}$$

and the pressure ratio acreoo the turbine considering isentropic efficiency:

$$P_{45} = P_4\left(1 - \frac{1 - T_{45}/T_4}{\eta_{HPT}}\right)^{\frac{\gamma_{hot}}{\gamma_{hot}-1}}$$

Fig. 3. The turbofan HP spool model modification by ChatGPT for HPT cooling

The task was only partially completed. The mass flow after the compressor was corrected by reducing it for the bleed, but it was not added to the main flow at the high-pressure turbine (HPT). The energy change caused by the addition of the cooling fluid was not accounted for in the turbine's work calculations. The example of HPT spool calculation modification by ChatGPT for request fulfilment is presented in Fig. 3

Due to the need for further tedious work with the system to fix the model, the decision was made to withdraw from implementing these changes into the model.

Semi-perfect gas model

The next step involved an attempt to modify the gas properties in the engine model presented by ChatGPT. ChatGPT was requested to incorporate a semi-perfect gas model into the engine calculations and to provide references for the adopted model.

A model was introduced in which gas properties, such as specific heat and the isentropic exponent, were defined as functions of gas temperature, while the individual gas constant was assumed to be a constant value. The source of the applied model was indicated as reference [24], which contains a formulation for the variation of specific heat expressed as a polynomial. The model for calculating specific heat applied by ChatGPT was a 4th degree polynominal:

$$Cp(T) = R(A + BT + CT^2 + DT^3 + ET^4) \qquad (2)$$

The polynomial coefficients proposed by ChatGPT are presented in Table 4 where: R – individual gas constant in [J/kg/K] and T – temperature in [K].

Table 4. Polynomial coefficient proposed by ChatGPT

Coefficient	Value
A	0.992313
B	0.236688
C	–0.048898
D	0.004388
E	–0.000106

ChatGPT then prepared Matlab functions for calculating the specific heat: get_cp, isentropic exponent get_gama, and individual gas constant get_R as temperature-dependent variables, and implemented the necessary modifications in the engine model to use these functions for gas parameter calculations.

The gas model, which, according to ChatGPT was dedicated to air, was implemented for calculations involving both air and exhaust gases. However, a different approach was applied: in calculations for the cold flow, the values of cp and gama were computed based on the inlet temperature of each engine component. In contrast, for the hot flow (turbines), cp was calculated at the inlet temperature and used to determine the outlet temperature, while gama was computed for the mean temperature and used to calculate the outlet pressure. A code snippet illustrating this part of ChatGPT algorithm is shown in Fig. 4. According to the literature [4, 7], the recommended approach in this regard is to use the mean temperature to determine the gas properties used in the calculations for each individual component. This approach requires the application of iterative calculations.

```
% High-Pressure Compressor (HPC) exit conditions
cp_cold = get_cp(T25);
gamma_cold = get_gamma(T25);
P3 = P25 * HPCPR;
T3 = T25 * (1 + (1/eta_hpc) * (HPCPR^((gamma_cold-1)/gamma_cold) - 1));

% Pressure drop in the burner
P4 = P3 * pi_b;

% Fuel-Air Ratio (FAR) with burner efficiency
cp_hot = get_cp(TIT);
LHV = 43e6;  % J/kg (jet fuel lower heating value)
FAR = cp_hot * (TIT - T3) / (eta_b * LHV);

% High-Pressure Turbine (HPT) calculations
cp_cold = get_cp(T3);
h_hpt = cp_cold * (T3 - T25) / eta_mech_hpt;
T45 = TIT - h_hpt / cp_hot;
gamma_hot = get_gamma((TIT + T45) / 2);
P45 = P4 * (1 - (1 - (T45/TIT)) / eta_hpt)^(gamma_hot / (gamma_hot - 1));
```

Fig. 4. Matlab code for HP shaft components calculation

To address this issue, ChatGPT was first asked to introduce a combustion gas model for calculations in the turbine and exhaust nozzle, taking into account that the working fluid in these sections is the product of hydrocarbon fuel combustion, with the fuel-air mass flow rate being approximately 2% relative to the mass flow rate of the air. This level of fuel burnt mass to airflow mass ratio is typical for turbofan engines and is used in numerous sources in the literature [4, 8, 23, 24].

ChatGPT proposed the model given in Equation (3), where the gas constant R and constant pressure heat value Cp are expressed in [J/kg/K], and the isentropic exponent gama is dimensionless. Based on the provided equations, it developed functions which were then implemented into the engine's computational model.

$$\begin{gathered} \mathrm{R} = 291 \\ \mathrm{Cp(T)} = 1100 + 0.1\,\mathrm{T} - 10^{-5}\,\mathrm{T}^2 + 10^{-9}\,\mathrm{T}^3 \\ \mathrm{gama} = \mathrm{Cp}/(\mathrm{Cp} - \mathrm{R}) \end{gathered} \tag{3}$$

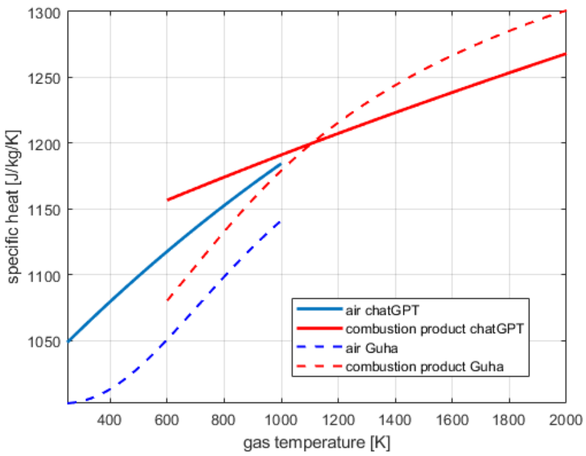

Fig. 5. The results of the specific heat calculations for the gas model proposed by ChatGPT and determined according to the model in [7] for air and combustion product of fuel/air ratio 0.02

To verify the provided equations, a comparison was made with the model presented in [7], which is consistent with the model from reference [24], cited by ChatGPT as the source material. The comparison of the specific heat calculations for air and exhaust gases produced for a mass ratio of 2% fuel to air in the temperature range occurring in a turbofan engine is shown in Fig. 5. The differences in the calculated values are evident, as well as a different pattern of changes in the resulting curves, especially for combustion products.

ChatGPT implemented a semi-perfect gas model across the entire engine simulation by introducing additional functions to compute gas properties. In the case of compressors, the model determined gas parameters based on the inlet temperature to each compressor stage. These values were then used to calculate the component's thermodynamic performance and the properties of the airflow downstream.

For turbines, the methodology applied was inconsistent. While the enthalpy drop across the compressor was calculated using the specific heat evaluated at the mean temperature consistent with standard engineering practices, ChatGPT applied varying approaches in the turbine section. In some cases, gas properties such as specific heat and the isentropic exponent were determined based on the inlet temperature (Fig. 6 underscore red line); in other instances, these properties were evaluated at the average temperature across the component (Fig. 6 underscore yellow line), and sometimes they were assessed according outlet temperature (Fig. 6 underscore green line). Notably, in certain sections of the engine model, both approaches were used simultaneously for different thermodynamic parameters within the same control volume, leading to internal inconsistencies in the treatment of gas properties.

```
% Fuel-Air Ratio (FAR) with burner efficiency
cp_hot = get_cp_gas(TIT);  % Use combustion gas model
LHV = 43e6;  % J/kg (jet fuel lower heating value)
FAR = cp_hot * (TIT - T3) / (eta_b * LHV);

% High-Pressure Turbine (HPT) calculations
cp_cold = get_cp(T3);
h_hpt = cp_cold * (T3 - T25) / eta_mech_hpt;
T45 = TIT - h_hpt / cp_hot;
gamma_hot = get_gamma_gas((TIT + T45) / 2);  % Use combustion gas model
P45 = ...
    P4 * (1 - (1 - (T45/TIT)) / eta_hpt)^(gamma_hot / (gamma_hot - 1));

% Low-Pressure Turbine (LPT) calculations
cp_cold = get_cp((T25 + T02) / 2);
h_lpt = (cp_cold * (T25 - T02) + (1 + BPR) * cp_cold * (T2 - T02)) ...
    / eta_mech_lpt;
T5 = T45 - h_lpt / cp_hot;
gamma_hot = get_gamma_gas((T45 + T5) / 2);  % Use combustion gas model
P5 = ...
    P45 * (1 - (1 - (T5/T45)) / eta_lpt)^(gamma_hot / (gamma_hot - 1));
```

Fig. 6. Code section implementing semi perfect gas model in the performance calculation for the high-pressure and low-pressure turbines

According to literature [4, 7], the recommended methodology for such thermodynamic simulations involves computing the average specific heat for each component and then using it to derive other gas properties. ChatGPT's implementation deviated from this standard, resulting in inconsistencies in the application of gas property models across engine components. It also influenced the calculation results, which are given in Table 5 after using the model generated by ChatGPT.

It can be observed that, despite the previously identified shortcomings in the model formulation, the results deviate only slightly from the expected values. The thrust is marginally lower than the value obtained in the earlier model (see Table 3) and is 1.8% higher than the results of the "correct model", but it remains within the range specified by the manufacturer (see Table 2). The specific fuel consumption increased to a value outside the manufacturer's specified range, exceeding the maximum limit by nearly 9%. Eliminating the identified modeling deficiencies would undoubtedly improve these results, which are already reasonably close to the actual values. A discussion with ChatGPT was conducted to address this issue; however, the implemented modifications did not yield the desired improvements, and further attempts to correct the model were therefore discontinued in this research.

Table 5. Calculation results for the model generated by ChatGPT with the semi-perfect gas model

Parameter	ChatGPT semi perfect gas model
Takeoff thrust [kN]	102.4
TSFC [g/(kNs)]	11.67

4. Summary and conclusions

The conducted discussion with ChatGPT 4.0 focused on the progressive development and refinement of the turbofan engine performance model, incorporating both thermodynamic and gas property improvements. Starting from a simplified configuration, successive enhancements were introduced to account for non-ideal component efficiencies, realistic bypass and cooling flow modeling, and the implementation of a semi-perfect gas model with temperature-dependent properties.

Throughout the process, ChatGPT was able to generate computational model and provide explanations aligned with general engineering practice. However, numerous issues were encountered, particularly regarding consistent application of gas property calculations, correct distribution of work between turbines and compressors, and the handling of cooling and bleed flows. In several instances, the changes implemented by ChatGPT did not follow the provided instructions or introduced new errors, requiring precise step-by-step guidance and manual corrections.

Despite these challenges, the final model yielded results that were relatively close to those reported by engine manufacturers and validated by other verified simulation models. Thrust levels fell within the expected range, and specific fuel consumption, although slightly higher than desired, remained within an acceptable deviation considering the model limitations.

It was also observed that ChatGPT performed very reliably when implementing requested modifications into the numerical engine model. Its ability to translate instructions into functioning MATLAB code was consistently accurate and error-free.

In conclusion, while ChatGPT demonstrates a useful capacity for supporting the development of engine performance models, its effectiveness is limited by inconsistency in complex thermodynamic logic and a need for iterative correction when modeling advanced physical processes. This indicates that the data generated by ChatGPT is still not entirely trustworthy. They must be verified by experts, whose intervention is very often necessary to correct and eliminate errors.

As such, at the current stage of development, close user supervision and technical validation remain essential when using LLMs like ChatGPT for engineering design and analysis tasks. However, it is expected that these tools will become increasingly capable and reliable in supporting model development in the near future. Comparative studies between the performance of ChatGPT 3.5 and 4.0 at work show a significant improvement in task execution between these versions [30]; therefore, it is to be expected that the next version of the program will perform even better in this respect.

It should also be noted that the quality of user input – particularly well-structured prompts and precise instructions – plays a critical role in achieving accurate results. While the evolution of human–AI collaboration in this area holds significant potential, it was not the focus of the present study.

Nomenclature

BPR	bypass ratio
CPR	compressor pressure ratio
F	thrust
FAR	fuel air ratio
FPR	fan pressure ratio
h	enthalpy
LLMs	Large Language Models
OPR	overall pressure ratio
p	pressure
SFC	specific fuel consumption
T	temperature
TIT	turbine inlet temperature
TSFC	takeoff specific fuel consumption
V	velocity
W	work

Bibliography

[1] Bednarz A, Kabalyk K, Jakubowski R, Bartłomowicz R. Numerical study on sensitivity of turbofan engine performance to blade count of centrifugal compressor impeller. Energies. 2023;16(14):5251. https://doi.org/10.3390/en16145251

[2] Catana RM, Dediu G. Analytical calculation model of the TV3-117 turboshaft working regimes based on experimental data. Appl Sci. 2023;13(19):10720. https://doi.org/10.3390/app131910720

[3] CFM International. CFM56. Wikipedia. https://en.wikipedia.org/wiki/CFM_International_CFM56#cite_note-cfm56-2-61

[4] Cumpsty N, Heyes A. Jet propulsion: a simple guide to the aerodynamics and thermodynamic design and performance of jet engines. 3rd ed. Cambridge: Cambridge University Press 2015. https://doi.org/10.1017/CBO9781316223116

[5] Deng W, Xu Y, Ni M, et al. Multi-fidelity simulation of gas turbine overall performance by directly coupling high-fidelity models of multiple rotating components. J Therm Sci. 2024;33:1357-1378. https://doi.org/10.1007/s11630-024-1975-3

[6] Ege DN, Øvrebø HH, Stubberud V, Berg MF, Elverum C, Steinert M et al. ChatGPT as an inventor: eliciting the strengths and weaknesses of current large language models against humans in engineering design. Artificial Intelligence for Engineering Design, Analysis and Manufacturing. 2025; 39:e6. https://doi.org/10.1017/S0890060425000010

[7] Guha A. An efficient generic method for calculating the properties of combustion products. P I Mech Eng A-J Power Energy. 2001;215(3):375-387. https://doi.org/10.1243/0957650011538596

[8] Hill PG, Peterson CR. Mechanics and thermodynamics of propulsion. Reading, MA: Addison-Wesley 1965.

[9] Jakubowski R. Evaluation of performance properties of two combustor turbofan engine. Eksploat Niezawodn. 2015; 17(4):575-581. https://doi.org/10.17531/ein.2015.4.13

[10] Jakubowski R, Bednarz A, Rogalski Ł. Study of the effects of heat exchanger location on turbofan engine performance. Adv Sci Technol Res J. 2024;18(4):355-368. https://doi.org/10.12913/22998624/189464

[11] Jakubowski R, Jakliński P. A practical approach to modeling and performance analysis of a turboshaft engine using Matlab. Appl Sci. 2024;14(23):11373. https://doi.org/10.3390/app142311373

[12] Kabalyk K, Bednarz A, Kantyka K. Fatigue safety factor of a transonic centrifugal compressor impeller subject to blade thickness. Scientific Reports. 2025;15:18693. https://doi.org/10.1038/s41598-025-03776-0

[13] Kabashkin I, Misnevs B, Zervina O. Artificial intelligence in aviation: new professionals for new technologies. Appl Sci. 2023;13(21):11660. https://doi.org/10.3390/app132111660

[14] Kozakiewicz A, Ludwiczak A. Analysis of nitrogen oxide emissions generated by the F100-PW-229 turbine aircraft engine, performed using the gasturb software. Problems of Mechatronics Armament Aviation Safety Engineering. 2025;16(1):9-20. https://doi.org/10.5604/01.3001.0055.0333

[15] Krus P. Large language model in aircraft system design. Proceedings of the 34th Congress of the International Council of the Aeronautical Sciences; 2024. Florence. https://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-211541

[16] Kulczycki A, Przysowa R, Białecki T, Gawron B, Jasiński R, Merkisz J et al. Empirical modeling of synthetic fuel combustion in a small turbofan. Energies. 2024;17(11): 2622. https://doi.org/10.3390/en17112622

[17] Kuźniar M, Pawlak M, Orkisz M. Comparison of pollutants emission for hybrid aircraft with traditional and multi-propeller distributed propulsion. Sustainability. 2022; 14(22):15076. https://doi.org/10.3390/su142215076

[18] Maciorowski D, Ludwiczak A, Kozakiewicz A. Hydrogen, the future of aviation. Combustion Engines. 2024;197(2): 126-131. https://doi.org/10.19206/CE-178375

[19] Loryś SM, Orkisz M. Neural network approach to compressor modelling with surge margin consideration. Archives of Thermodynamics. 2022;43(1):89-108. https://doi.org/10.24425/ather.2022.140926

[20] Majka A, Muszyńska-Pałys J. Analysis of the performance of an aircraft powered by hybrid propulsion. Combustion Engines. 2023;193(2):45-51. https://doi.org/10.19206/CE-161107

[21] Marszałek N. Performance analysis of turbofan engine with additional combustion chamber fueled by alternative fuel. Combustion Engines. 2019;179(4):249-253. https://doi.org/10.19206/CE-2019-441

[22] Marszałek N. The impact of thermodynamics parameters of turbofan engine with ITB on its performance. Combustion Engines. 2020;182(3):16-22. https://doi.org/10.19206/CE-2020-303

[23] Mattingly JD, Boyer KM. Elements of propulsion: gas turbines and rockets. 2nd ed. Reston, VA: American Institute of Aeronautics and Astronautics 2016.

[24] McBride BJ, Zehe MJ, Gordon S. NASA Glenn coefficients for calculating thermodynamic properties of individual species. Cleveland, OH: NASA Glenn Research Center 2002.

[25] Muchowski R, Gubernat SM. Influence of axial compressor model simplification and mesh density on surge margin evaluation. Adv Sci Technol Res J. 2021;15(3):243-253. https://doi.org/10.12913/22998624/140541

[26] Pasieka M, Grzesik N, Kuźma K. Simulation modeling of fuzzy logic controller for aircraft engines. Int J Comput. 2017;16:27-33. https://doi.org/10.47839/ijc.16.1.868

[27] Pawlak M, Kuźniar M. Performance and emission of the aircraft with hybrid propulsion during take-off operation cycle. Adv Sci Technol Res J. 2024;18(1):155-166. https://doi.org/10.12913/22998624/177254

[28] Pierson KC, Ha MJ. Usage of ChatGPT for engineering design and analysis tool development. AIAA SCITECH 2024 Forum. 2024; Orlando, FL. Reston, VA: American Institute of Aeronautics and Astronautics. https://doi.org/10.2514/6.2024-0914

[29] Pradas Gómez A, Krus P, Panarotto M, Isaksson O. Large language models. Proceedings of the Design Society. 2024; 4:2197-206. https://doi.org/10.1017/pds.2024.222

[30] Pradas Gómez A, Panarotto M, Isaksson O. Evaluation of different large language model agent frameworks for design engineering tasks. Proceedings of the NordDesign 2024; 2024; Reykjavik, Iceland. Glasgow, UK: The Design Society. 2024:693-702. https://doi.org/10.35199/NORDDESIGN2024.74

[31] Romagnosi L, Li YC, Mezine M, Teixeira, M, Vilmin S, Anker JE et al. Methodology for steady and unsteady full-engine simulations. Proceedings of the ASME Turbo Expo 2019 Turbomachinery Technical Conference and Exposition. Phoenix, USA, 17–21 June 2019.

[32] Timperley LR, Berthoud L, Snider C, Tryfonas T. Assessment of large language models for use in generative design of model based spacecraft system architectures. J Eng Des. 2025;36(4):550-570. https://doi.org/10.1080/09544828.2025.2453401

[33] Ventosa-Molina J, Lange M, Mailach R, Fröhlich, J. Study of relative endwall motion effects in a compressor cascade through direct numerical simulations. ASME J Turbomach. 2021;143(1):011005. https://doi.org/10.1115/1.4049101

[34] Wang L, Chou J, Zhou X, Tien A, Baumgartner DM. AviationGPT: a large language model for the aviation domain. AIAA SciTech. 2024. https://doi.org/10.48550/arXiv.2311.17686

[35] Wygonik P. Dobór zespołu napędowego do samolotu wielozadaniowego według kryterium zadania lotniczego (in Polish). Oficyna Wydawnicza Politechniki Rzeszowskiej. Rzeszów 2024.

Robert Jakubowski, DEng. – Aerospace Technology Department, Rzeszów University of Technology, Poland.

e-mail: *robert.jakubowski@prz.edu.pl*

Marek Szumski, DEng. – Aerospace Technology Department, Rzeszów University of Technology, Poland.

e-mail: *marek.szumski@prz.edu.pl*