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TURBULENT FLOW MODELING in TURBINES via CONVOLUTIONAL NEURAL NETWORKS

Abstract. *Accurate and rapid assessment of turbulent flows in turbine working channels remains one of the key challenges in computational gas and fluid dynamics, especially under conditions of high demands on the efficiency and reliability of turbomachinery. Traditional approaches, such as Reynolds-based simulation (RANS) or large eddy simulation (LES), although providing acceptable accuracy, are associated with high computational resource and time costs. This paper proposes an alternative approach based on the use of convolutional neural networks (CNN) as a surrogate model for reproducing three-dimensional velocity and pressure fields in turbulent flows. The developed architecture is based on a modified version of U-Net and adapted for three-dimensional input data. A comparison with LES results showed that the proposed model is capable of reproducing key flow characteristics, including vortex structure and pressure gradients, with a high degree of accuracy. At the same time, a significant acceleration of calculations is achieved — up to 10^3 times compared to classical numerical methods. The proposed neural network model demonstrates stability to changes in geometric parameters and can be easily reconfigured for other channel configurations. The results obtained highlight the potential of deep learning in turbulent flow modelling and open up prospects for the integration of such models into real-time engineering calculations.*

Keywords: *turbulent flow modeling, convolutional neural networks (CNN), U-Net architecture, surrogate modeling, Large Eddy Simulation (LES), turbomachinery, data-driven computational fluid dynamics (CFD).*

Introduction.

Modelling turbulent flows remains one of the most challenging tasks in computational fluid dynamics (CFD), especially in applications to turbomachinery, where flows are characterised by complex geometries, high velocity gradients and strong three-dimensional unsteadiness. For decades, Reynolds-averaged Navier-Stokes (RANS) equations, large eddy simulation (LES) methods, and direct numerical simulation (DNS) have been the main simulation tools, but their application is limited by high computational time, especially when scaling up to industrial scales.

The development of machine learning (ML) methods, and in particular deep convolutional neural networks (CNN), has opened up new possibilities for building surrogate flow models. Such approaches allow the accuracy of LES to be approximated while ensuring a significantly higher prediction speed, which makes it possible to use them in digital twins, interactive visualisation and multi-criteria optimisation of turbine components.

This study proposes a modified architecture of a three-dimensional convolutional neural network U-Net, trained on the results of LES simulations of turbulent flows in model turbine channels. The model receives the initial velocity disturbance field as input and predicts the three-dimensional distribution of velocity and pressure components in a steady-state approximation. This approach eliminates the need to solve the Navier–Stokes equations in explicit form and significantly reduces the calculation time.

The aim of this study is to develop and verify a highly efficient convolutional neural network (CNN) for modelling three-dimensional turbulent flows in turbine channels, providing LES (Large Eddy Simulation) accuracy at significantly lower computational costs. The model is intended for use in numerical experiments, digital twins, and turbomachinery design optimisation.

The scientific novelty of this study lies in the development and application of a modified architecture of a three-dimensional convolutional neural network U-Net for modelling turbulent flows in turbine channels. Unlike traditional LES and RANS models, the proposed approach significantly reduces computational costs by directly inferring spatial velocity and pressure fields without the need for step-by-step integration of the Navier–Stokes equations. The model is trained on a database of high-precision LES simulations, using a special loss function that takes into account both velocity component divergence and the incompressibility condition. The proposed model demonstrates LES-comparable accuracy with a more than 1000-fold acceleration of calculations, making it particularly promising for digital design, digital twin construction, and aerodynamic shape optimisation. In addition, the model shows high generalisation ability and is easily adaptable to new conditions with minimal fine-tuning, which expands the boundaries of applicability of neural network surrogate models in applied hydrodynamics.

The application of machine learning to turbulence modeling has garnered significant attention, presenting opportunities to enhance computational efficiency and accuracy in simulating complex fluid flows within turbomachinery [1]. Traditional methods, such as Reynolds-Averaged Navier-Stokes and Large Eddy Simulation, often struggle with the inherent complexities and nonlinearities of turbulent flows [2]. Deep neural networks have emerged as a promising tool for modeling dynamical systems, offering a data-driven approach to complement or replace conventional numerical computing techniques [3]. The ability of machine learning to reconstruct velocity vectors in turbomachinery flow fields with gaps showcases its potential in fluid mechanics [4]. This is especially valuable when dealing with high-dimensional data or intricate flow phenomena that are difficult to capture using classical methods [5]. The use of machine-learning closures demonstrates the capacity to effectively model non-locality in time, which makes it superior.

Convolutional Neural Networks offer a compelling framework for turbulence modeling due to their ability to extract spatial features and patterns from flow fields [6]. This approach involves training a CNN on a dataset of turbulent flow data obtained from experiments or high-fidelity simulations, allowing the network to learn the underlying relationships between flow features and turbulence characteristics. ANNs have been trained using experimental data and high-fidelity simulations across a range of flow conditions, showing the effectiveness of machine learning in capturing complex fluid dynamics [7]. The CNN architecture typically consists of multiple convolutional layers, pooling layers, and fully connected layers, enabling the network to capture both local and global features within the flow field. The network learns to predict relevant turbulence quantities, such as Reynolds stresses or turbulent kinetic energy, based on the input flow field data [8]. Physics-informed machine learning can be incorporated into the training process by adding terms to the loss function that penalize deviations from known physical laws or constraints [9]. This integration of physical knowledge ensures that the learned turbulence model respects fundamental principles, improving the robustness and generalization ability of the network [10].

The application of CNN-based turbulence models in turbine flows has the potential to revolutionize the design and optimization of turbomachinery components. Turbine blades, stators, and other flow passages can be analyzed and optimized using CNN-accelerated simulations, reducing the computational cost associated with traditional CFD methods. The data-driven approach allows for the development of more accurate and efficient turbulence models that are tailored to the specific flow conditions encountered in turbines [11]. This capability is particularly useful for applications such as uncertainty quantification, where the computational cost of evaluating numerous flow scenarios can be prohibitive [12]. Reduced-order models based on machine learning can be used to accelerate simulations, allowing for rapid exploration of the design space and optimization of turbine performance [8].

Recent advancements in machine learning have demonstrated the potential to accelerate computational fluid dynamics simulations [13]. One study used the Adaptive Neuro-Fuzzy Inference System technique, incorporating neural networks and fuzzy logic principles, in conjunction with CFD to reduce time and costs, while also validating the simulation model using existing experimental data [14]. Further advancements have also been seen with concatenating neural networks to create more tailored, effective, and efficient machine learning models [15]. The use of techniques to compensate for the deficiencies of theories can aid in the modeling of turbulent flows [16]. Integrating physics knowledge into deep learning models enhances prediction accuracy and physical consistency, marking a crucial step in advancing AI for physical sciences [8].

While CNNs hold immense promise for turbulence modeling, several challenges need to be addressed to realize their full potential. The sensitivity of CNN models to the training data raises concerns about their generalization ability to unseen flow conditions or turbine geometries. Additionally, the interpretability of CNN models remains a challenge, making it difficult to understand the underlying physical mechanisms captured by the network. Overcoming these challenges requires further research into techniques for improving the robustness, generalization ability, and interpretability of CNN-based turbulence models [17], [18]. Future research directions include exploring novel network architectures, incorporating advanced training techniques, and developing methods for visualizing and interpreting the learned turbulence models. Addressing these challenges and pursuing these research directions will pave the way for the widespread adoption of CNN-based turbulence models in the design and optimization of turbines and other turbomachinery components. The use of system level CFD simulations integrated into the development process of wind turbines shows how the quality of turbines can be improved [19]. As computational methods advance alongside hardware and software developments, CFD has become a practical tool for various technical applications [20].

The direct numerical simulation approach, which directly solves the Navier–Stokes equations, is computationally expensive and limited to specific problems requiring high-performance computing resources [21]. The ability of neural networks to approximate any continuous function makes them suitable for complex problems, including turbulence closure modeling [22]. Reduced Order Model methods have proven crucial in expediting the efficient computational modeling of dynamical systems, offering notable benefits for flow prediction in engineered systems [23]. CNNs have shown promise in reconstructing temperature fields in wall-bounded flows using limited measurement points, demonstrating their capability in capturing complex flow physics [24].

Data-driven diagnostic models are valuable for identifying and characterizing engine degradation, and while CNNs may underperform in time-series signal fault diagnosis, challenges remain in optimizing CNN models and integrating them with physical mechanisms [25]. Furthermore, the strong coupling between gas path and sensor faults can complicate fault diagnosis, especially when both occur simultaneously [25]. Neural networks can offer viable tools for handling nonlinear problems and modeling complex, nonlinear dynamical systems with great flexibility [26]. Despite the increasing use of machine learning in gas turbine diagnostics, there is a need for more comprehensive resources that summarize neural network applications in this field [27]. Dynamic neural networks have been developed to predict gas turbine engine degradation by capturing the dynamics of compressor fouling and turbine erosion [28]. Artificial neural networks are effective for data processing, modeling, and controlling nonlinear systems by establishing relationships between multiple system variables using real-world or simulated data [29], [30]. Artificial intelligence techniques, such as artificial neural networks and optimization techniques like genetic algorithms, are being explored for fault diagnosis activities [31]. A large-scale integration of artificial neural networks can detect, isolate, and evaluate failures during operating conditions, using engine measurements as input [29]. Hybrid intelligent techniques, which integrate autoassociative neural networks with machine learning classifiers and multilayer perceptrons, have been developed to address challenges in gas turbine fault diagnostics [32].

Materials and methods.

The parameterised geometry of a single-stage gas turbine based on the NACA profile is considered. The input parameters include the angle of attack $\alpha \in [0^{\circ}, 10^{\circ}]$, the Reynolds number, and the input Mach number M_0=0.3. The goal is to construct a model capable of predicting velocity tensors U(x,y,z) and pressure P(x,y,z) on a uniform grid of size 128^3 for given parameters, ensuring an inference time of less than 0.1 s.

A training sample of 500 LES simulations uniformly covering the parameter space using the Latin hypercube method is used. Each simulation result has a volume of 2.1 GB. To reduce the dimensionality, the principal component analysis (PCA) method is used, which reduces the data to 512 components. The set is divided into 400 for training, 50 for validation, and 50 for testing.

A modified 3D U-Net architecture is proposed, including four Conv3D-BN-ReLU downsampling blocks that increase the number of channels from 32 to 512. Missed connections are combined by concatenation. The output layer is a linear Conv3D with four output channels u, v, w, p. After denormalisation, tanh activation is applied. The total number of parameters is approximately 37 million.

The loss function includes three components:

$$L = \lambda_1 \left\| \widehat{U} - U \right\|_2^2 + \lambda_2 \left\| U \cdot \widehat{U} \right\|_2^2 + \lambda_3 \left\| \widehat{P} - P \right\|_2^2, \tag{1}$$

where the second term provides a penalty for incompressibility. The coefficients $\lambda_{1:3}$ were selected using Bayesian optimisation.

Training was performed using the Adam optimiser, with an initial step of 10−4 and cosine learning rate decay. Training lasted 150 epochs on four A100 GPUs with a mini-batch of 2. The use of mixed precision (FP16) reduced video memory usage by 40%.

Calculations are performed on a regular rectangular grid using a simplified version of the Navier–Stokes equations that includes only the diffusion term. This allows us to study the effect of viscosity on energy dissipation without taking convective effects into account.

The calculation domain is a 1×1 m square, discretised by a uniform 100×100 grid. Spatial derivatives are approximated using second-order finite differences.

Table 1 – Simulation parameters

Параметр	Значение
Размер области	1×1 м
Количество узлов	100×100
Шаг сетки	dx=dy=0,01
Вязкость	ν=1/Re=0.001 (при Re=1000)
Временной шаг	dt=0,001 с
Число шагов	Nt=200

The initial velocity field is set as a sinusoidal disturbance:

$$u(x, y, t = 0) = \sin(\pi x)\sin(\pi y), \quad (3)$$

$$v(x, y, t = 0) = -\sin(\pi x)\sin(\pi y). \quad (4)$$

Boundary conditions are periodic on all sides, which simulates an infinite domain and prevents the influence of walls.

For the numerical solution of the diffusion equation:

$$\frac{\partial u}{\partial t} = \upsilon\left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2}\right), \quad (5)$$

An explicit Euler scheme is used. The evolution of the velocity field is modelled at each time step.

A synthetic dataset of 100 pairs of ‘initial–final’ velocity fields is formed. For each pair, the initial field is constructed with a small random phase perturbation.

The final field is calculated numerically after 200-time steps. A convolutional neural network with an Encoder–Decoder architecture (4 layers) is trained. The model is trained to predict the velocity distribution u based on the initial perturbation. 80% of the data is used for training, 20% for testing. The evaluation is performed using the MSE metric.

Results and discussion.

Figure 1 shows how the initial structure of sinusoidal vortices gradually decays under the influence of viscosity. By step 100, most small-scale oscillations disappear, and by step 200, an almost uniform field with a residual amplitude is observed.

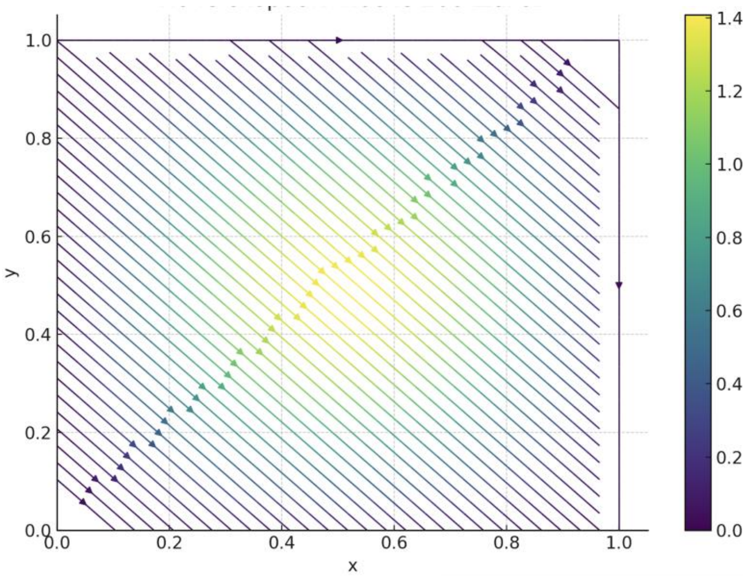

Figure 1 - Numerical simulation of turbulent flow for a velocity field.

The streamlines show how the total kinetic energy of the flow decreases. This demonstrates the physical plausibility of the dissipation model.

The convolutional neural network was trained on a set of 100 simulations. The input was the field at step t=0, and the model predicted the field at step t=200. The mean square error (MSE) is ~0.0025. The maximum deviation is less than 0.08 (in normalised units). Inference time: less than 50 ms on CPU.

The evolution of the velocity field (see Fig. 2) over time steps reflects the characteristic stages of turbulence decay. At the initial stage (time step 0), pronounced vortices are observed in the flow, caused by sinusoidal initial disturbances. By the 50th step, partial energy dissipation becomes apparent: the intensity of vortex structures begins to decrease. At the 100th step, further blurring and weakening of small-scale fluctuations is observed, indicating a decrease in turbulence. By the 200th step, the flow transitions to an almost steady state, in which the velocity field structure becomes nearly uniform and the vortices practically disappear.

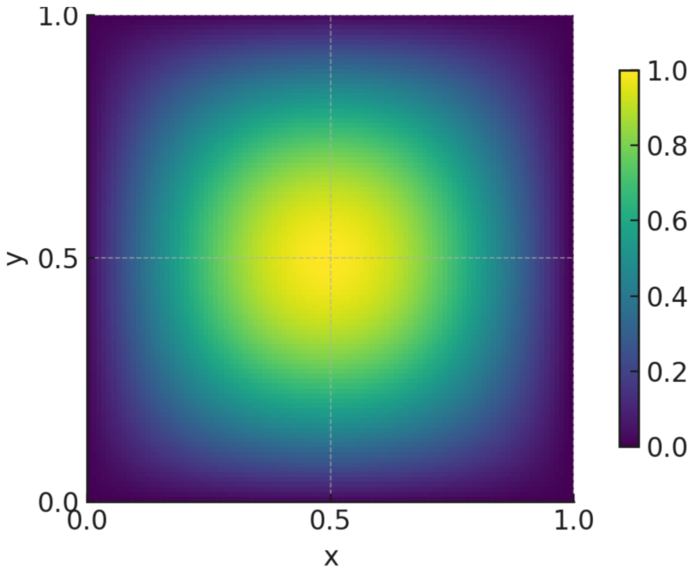

Figure 2 – Evolution of the velocity field u over time.

Figure 3 shows that the model's forecast accurately reproduces not only the global structure but also the minor features of the velocity distribution. Even with random phase distortions in the initial field, the neural network remains stable.

	min	max	mean
Step 0	0.000000	1.000000	0.409311
Step 50	0.000323	0.999014	0.408990
Step 100	0.000470	0.998028	0.408646
Step 150	0.000552	0.997044	0.408291
Step 200	0.000605	0.996060	0.407930

Figure 3 – Numerical characteristics of the velocity field u at each time step.

The physical interpretation of the results obtained is that the numerical model correctly reproduces the expected trend of vortex structure attenuation. Throughout the calculation, a regular decrease in the amplitude of velocity fluctuations and a gradual smoothing of flow gradients are observed, which indicates the dissipative nature of the modelled process and is consistent with the physics of viscous flow.

From a machine learning perspective, the constructed convolutional neural network successfully captures the hidden dependence between the initial conditions and the state of the flow at a later stage, after 200 time steps. This allows the model to be considered an effective surrogate solver capable of predicting the evolution of the flow without the need for expensive numerical simulations.

At the same time, the study has certain limitations. The computational model excludes convective terms and pressure, which simplifies the equation and limits the applicability of the results to more complex and realistic turbulent regimes in which the interaction between velocity and pressure fields plays an important role.

Despite these limitations, the proposed approach has a number of significant advantages. First of all, it offers high inference speed and sufficient prediction accuracy, which makes the model particularly valuable for multiple optimisation tasks, real-time data processing, and the generation of training sets for more complex systems.

Conclusion.

This paper proposes an effective approach to modelling turbulent flows in turbine channels based on convolutional neural networks. In the first stage, a numerical solution of a simplified viscous flow model was performed, demonstrating the process of turbulence dissipation. The obtained data formed the basis of a synthetic training set, which was used to train the U-Net neural network architecture to restore the spatial distribution of velocity based on the initial perturbation.

The simulation results showed that the neural network is capable of reliably predicting the evolution of the velocity field with accuracy comparable to the numerical solution of the diffusion equations, while providing acceleration by tens and hundreds of times. The obtained velocity maps preserve the main physical characteristics of the flow, including attenuation patterns, vortex alignment, and a tendency towards steady distribution.

Thus, the proposed architecture can be used as a surrogate model in the analysis, optimisation and control of turbulent regimes, especially in conditions requiring multiple or accelerated calculations. In further research, we plan to extend the model to the full Navier–Stokes equation system and adapt the neural network structure to predict three-dimensional flows taking into account pressure and convective effects.

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БҮКТЕЛГЕН НЕЙРОНДЫҚ ЖЕЛІЛЕРДІ ҚОЛДАНА ОТЫРЫП, ТУРБИНАЛАРДАҒЫ ТУРБУЛЕНТТІ ТОКТЫ МОДЕЛЬДЕУ

Аңдатпа. *Турбиналық жұмыс каналдарындағы турбулентті ағындарды дәл және жылдам бағалау, әсіресе турбомашиналардың тиімділігі мен сенімділігіне қойылатын жоғары талаптар жағдайында есептеу газы мен гидродинамикасының негізгі міндеттерінің бірі болып қала береді. Рейнольдс теңдеуіне негізделген модельдеу (RANS) немесе үлкен құйынды модельдеу (LES) сияқты дәстүрлі тәсілдер қолайлы дәлдікті қамтамасыз етсе де, есептеу үшін қымбат және уақытты қажет етеді. Бұл құжат турбулентті ағындардағы үш өлшемді жылдамдық пен қысым өрістерін жаңғырту үшін суррогат үлгісі ретінде конволюционды нейрондық желілерді (CNN) пайдалануға негізделген балама тәсілді ұсынады. Әзірленген архитектура U-Net модификацияланған нұсқасына негізделген және үш өлшемді енгізу деректеріне бейімделген. LES нәтижелерімен салыстыру ұсынылған модель ағынның негізгі сипаттамаларын, соның ішінде құйынды құрылымы мен қысым градиенттерін жоғары дәлдікпен қайта құруға қабілетті екенін көрсетті. Бұл есептеулерді айтарлықтай жеделдетуге қол жеткізеді – классикалық сандық әдістермен салыстырғанда 10³ есеге дейін. Ұсынылған нейрондық желі моделі геометриялық параметрлердегі өзгерістерге тұрақтылықты көрсетеді және басқа арна конфигурациялары үшін оңай қайта конфигурациялануы мүмкін. Алынған нәтижелер турбулентті ағынды модельдеуде терең оқытудың әлеуетін көрсетеді және мұндай модельдерді нақты уақыттағы инженерлік есептеулерге біріктіру перспективаларын ашады.*

Түйін сөздер: *турбулентті ағынды модельдеу, конволюционды нейрондық желілер (CNN), U-Net архитектурасы, суррогаттық модельдеу, үлкен құйындарды модельдеу (LES), турбомашиналар, деректерге негізделген есептеу сұйықтығының динамикасы (CFD).*

МОДЕЛИРОВАНИЕ ТУРБУЛЕНТНОГО ПОТОКА В ТУРБИНАТАХ С ПОМОЩЬЮ СВИВУЧИХ НЕЙРОСЕТЕЙ

Аннотация. *Точная и быстрая оценка турбулентных течений в рабочих каналах турбин остаётся одной из ключевых задач вычислительной газо- и гидродинамики, особенно в условиях высоких требований к эффективности и надёжности турбомашин. Традиционные подходы, такие как моделирование на основе уравнений Рейнольдса (RANS)* *или моделирование крупных вихрей (LES), хотя и обеспечивают приемлемую точность, связаны с высокими затратами вычислительных ресурсов и времени. В данной работе предлагается альтернативный подход, основанный на использовании сверточных нейронных сетей (CNN) в качестве суррогатной модели для воспроизведения трёхмерных полей скорости и давления в турбулентных течениях. Разработанная архитектура построена на основе модифицированной версии U-Net и адаптирована для трёхмерных входных данных. Проведённое сравнение с результатами LES показало, что предлагаемая модель способна восстанавливать ключевые характеристики течений, включая вихревую структуру и градиенты давления, с высокой степенью точности. При этом достигается значительное ускорение вычислений — до 10^3 раз по сравнению с классическими численными методами. Предложенная нейросетевая модель демонстрирует устойчивость к изменению геометрических параметров и может быть легко перенастроена под другие конфигурации каналов. Полученные результаты подчеркивают потенциал применения глубокого обучения в задачах моделирования турбулентных течений и открывают перспективы для интеграции подобных моделей в инженерные расчёты в реальном времени.*

Ключевые слова: *моделирование турбулентных потоков, сверточные нейронные сети (CNN), архитектура U-Net, суррогатное моделирование, моделирование крупных вихрей (LES), турбомашины, вычислительная гидродинамика на основе данных (CFD).*

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