Deep learning for CFD analysis in built environment applications: a review

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Abstract. The study and control of the airflow in indoor environment is of great importance since it directly affects human daily life primarily in terms of health and comfort. Fast and accurate airflow predictions are therefore desirable when it comes to built environment applications of inverse design, system control, evaluation, and management. Computational fluid dynamics (CFD) enables detailed predictions through numerical flow simulations and it has been consistently used to simulate airflow motion, heat transfer, and contaminant transport in indoor environment. However, CFD still faces many challenges mainly in terms of computational expensiveness and accuracy. With digitization, recent interest is posed on new data driven tools to either substitute CFD typically for faster predictions or aid the CFD simulation for improved accuracy. More specifically, the abilities of deep learning and artificial neural networks (ANN) as universal non-linear approximator, handling of high dimensionality fields, and computational inexpensiveness are very appealing. This work reviews current deep learning applications in built environment research, which are only limited to surrogate modeling as replacement for expensive CFD simulation. ANN enables fast and sometimes even real-time prediction, but usually at a cost of a degraded accuracy. For this reason, we also critically review what it is done and presented in fluid mechanics simulations research in general, to propose and inform about different techniques other than surrogate modeling for built environment applications and possibly improve the predictions quality as well. More precisely, ANNs can enhance the turbulence model in various way for coupled CFD simulations of higher accuracy, improve the efficiency of POD decompositions methods, leverage crucial physical properties and information with physics informed deep learning modeling, and even unlock new advanced methods for flow analysis such as super-resolution techniques. All these methods are very promising and largely yet to be explored in the built environment scene. Together with promising advancements, deep learning methods come with challenges to overcome, such as the availability of consistent large flow databases, the extrapolation task problem, and over-fitting, etc.

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1. Introduction

The advent of the era of digitization is enabling the use of machine learning tools to provide advances to many areas of research in scientific and engineering disciplines. Specifically, within machine learning, deep learning can leverage the growing amount of data available to infer predictions over a broad range of different problems, such as airflow simulations. Computational Fluid Dynamics (CFD) is a field where data driven models are showing much potential in the latest years [1]. Standard CFD deals with numerical simulations of fluid flows by solving physical flow equations. It is a useful, and widely used tool that enables detailed predictions. However, it has unfortunately some limitations, mainly in terms of computational expensiveness. The most accurate CFD approach that tries to fully capture turbulence phenomena of the flow, called *Direct Numerical Simulation* (DNS), is in fact still unfeasible in most practical applications due to the extremely high computational power required to solve the equations for the discretized grid. Other common CFD approaches are the so-called *Large Eddy Simulations* (LES) and *Reynolds Averaged Navier*

Stokes equations (RANS) methods. The latter in particular is significantly less computational demanding than DNS but introduces assumptions and turbulence models which eventually increase the number of uncertainties and lower the overall accuracy of the simulation [2]. Besides, the problem with CFD simulations in built environment is that, even with small indoor domain, the airflow is quite complex, making even RANS simulations quite demanding in processes where fast predictions and control are necessary. Even though very fast or real time predictions are unfeasible, RANS represents the industry standard and it is widely used in the indoor environment to simulate turbulent airflow [3], heat transfer [4], and contaminant transport [5]. It is also used in the urban environment to simulate wind flow around buildings [6] or at pedestrian level [7] and tracking pollutants [8]. While new improved CFD techniques, algorithms and models are appearing, recent interest is posed on new data driven tools, deep learning, to either substitute or aid CFD simulations. This work will review the current research on the interaction between built environment fluid dynamics simulations and deep learning algorithm. Deep learning is the supervised learning class based on *Artificial Neural Networks* (ANNs) [9], which task is to map the function between inputs and outputs. ANNs are composed of a number of hidden layers between input and output, Figure 1 shows an ANN in its most standard architecture: the *Multi-Layer Perceptron* (MLP) [9].

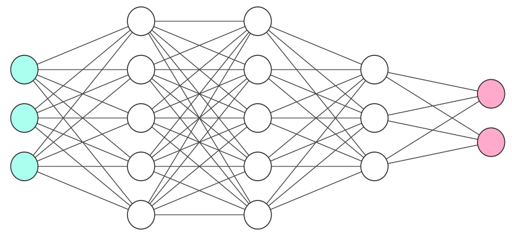

Fig. 1 - A four Layer MLP, with a 3 nodes input layer colored in light blue, 3 hidden layers of 5-5-3 nodes respectively in white, and a 2 nodes output colored in pink.

Applications with deep learning architectures of different types will be reviewed. Besides MLPs the most common to be found are *Convolutional Neural Networks* (CNNs) [10] and *Recurrent Neural Networks* (RNNs) [11]. CNNs are developed and adapted for computer vision tasks and pattern recognition. RNNs, instead, are specialized in working with time sequence data thanks to the presence of a feedback loop. In recent years, deep learning algorithm proved to be extremely flexible, highly scalable and universal approximator of non-linear functions, such as equations of the fluid flows.

2. Research Methods

The primary objective of this review paper is to inform and propose new interactions between built environment CFD simulations and deep learning algorithm. This interaction is not exactly new or never explored before. There are already some works that substitute CFD simulations with deep learning algorithm using the ANN as surrogate model of the numerical simulation, which are going to be reviewed in section 3. Surrogate modeling generally solves one of the main problems of CFD simulations being their general expensiveness. Depending on the specific problem, surrogate modeling can allow for order of magnitudes [12] faster airflow prediction, even **real-time** predictions in some cases [13]. However, the landscape of interaction is mostly limited to surrogate modeling, and what is generally wanted and desired is to obtain fast, but also accurate predictions of flow quantities such as velocity, pressure, temperature and pollutant concentrations to provide and control thermal comfort to indoor environments. Even though the main objective of surrogate modeling is to reduce computational cost while keeping the same order of accuracy [14], the computational inexpensiveness usually comes at the cost of degraded accuracy. Surrogate modeling is often built from and compared with RANS simulations, which still present all the uncertainties stated above. In the best cases ANNs produce very similar results in terms of accuracy, but worse in others. This review aims to show that surrogate modeling is not the only way to make use of deep learning architecture together with CFD simulations. By critically reviewing in section 4 some major applications of deep learning that have been attempted in fluid mechanics research, hints and opportunities for future research on integration of ANNs and CFD for built environment applications are proposed. The number and kind of deep learning interactions in fluid mechanics is in fact much larger allowing for a systematic review of different techniques such as turbulence model tuning and enhancement, surrogate modeling, POD, and super-resolution. Finally, section 5 offers a discussion about possible opportunities, but also challenges for deep learning methods to aid, substitute, or improve CFD simulations for the built environment.

3. Built Environment applications

Numerous indoor environment applications are strictly connected to the study and simulations of fluid flows. Fast and accurate predictions of variables such as velocity, pressure and temperature profiles are desirable in this context. Some examples of CFD simulations that are consistently performed in the indoor environment for inverse design are thermal comfort analysis, pollutant dispersion, HVAC system control, etc. For the outdoor environment, the simulations of wind and tracking pollutants are conducted at various urban levels. Thermal comfort in the indoor environment, such as vehicle cabins of cars but also aircraft is a challenging problem which has been attempted to solve with increased popularity by inverse design. Together with these methods, deep learning models have started to cover an important place in these applications. Deep learning techniques have already been widely applied since the early 2000s in specific topics such as building energy predictions [15,16,17] or HVAC system control [18,19]. However, data driven interactions with CFD simulations are still limited in quantity and diversity of approach. The vast majority of applications are limited to substituting surrogate modeling for expensive CFD simulations to achieve faster predictions. CFD simulations can in fact be very computationally demanding, especially in the design process, emergency management and control, where fast predictions are necessary, or in the outdoor environment where the simulation domain is usually large. The main objective of surrogate modeling is to reduce computational cost while keeping the same order of accuracy [14]. Section 3.1 reviews the studies on the topic.

3.1 Deep learning surrogate modeling in the built environment

In the work by Hintea et al. [13], from a minimalistic set of cabin environment sensors, several different machine learning algorithm, including a standard MLP network and a random forest algorithm, are used and compared to approximate equivalent temperature inside a car to obtain real-time predictions. The equivalent temperature is measured at eight body locations to provide a direct estimation of thermal comfort. Eventually the fastest prediction is delivered by a simpler linear regression model, while the MLP obtains the highest accuracy overall. As shown instead by other works (Zhang et al. [20,21] and Warey et al. [22] for instance), CFD simulations are not discarded completely, but still used as high fidelity solution necessary for training the deep learning algorithm. Warey et al. [22] (see Figure 2) use deep learning models to quantify the thermal comfort of indoor vehicle cabins for different boundary conditions of air temperature, but also air velocity, humidity, glazing conditions, etc. To better assess the indoor thermal comfort this time not only an equivalent temperature analysis is performed, but also on more advanced evaluation scores, the predicted mean vote and the predicted percentage of dissatisfied people. These scores evaluate thermal comfort from a more rational perspective [23]. CFD simulations previously validated with wind tunnel experimental measurements are generated to be used to train the deep learning algorithm, which was then applied also to different fields with real time predictions. Instead, Zhang et al. [20] first use a shallow standard MLP in general indoor environments with CFD as training data to solve the inverse design problem and identify a possible relationship between thermal comfort and inlet boundary condition. Later on in another work, Zhang et al. [21] apply the based knowledge on a simplified first class aircraft cabin environment. This time the deep learning surrogate model is integrated inside a genetic algorithm and the results are compared against a 57% more computationally expensive classic genetic algorithm without deep learning tools. Three shallow MLPs are singularly trained to obtain the predicted mean vote, the air age and the draft rate, the latter assessing the local discomfort for humans.

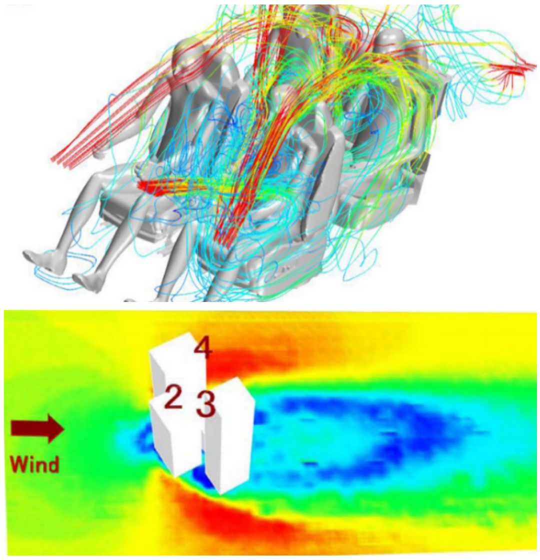

Fig. 2 - Two examples of deep learning surrogate modeling for built environment applications. Above the study of thermal comfort for indoor vehicles cabin by Warey et al. [22]. On the bottom, the optimization study of urban wind flow simulations by Tanaka et al. [12].

Upgrading the scale of simulations from indoor to external environments, like urban cities, accuracy deterioration and struggle to consider other boundary conditions such as traffic or weather are inevitable. Tanaka et al. [12] (see Figure 2), study urban flow simulations where the location, dimension and shape of four tall buildings were optimized in a restricted area with the construction of a CFD optimization tool. The objective is to reduce wind forces on buildings and mitigate local strong winds at pedestrian level. The focus of the paper still resides on CFD RANS simulations, which are eventually used to train a deep CNN encoder-decoder for *ultra-fast* (0.005 seconds) predictions. They estimate the CNN predictions to be about fifty thousand times faster than RANS. However, the ANN predictions show lack of accuracy compared to CFD simulations especially in specific case that the network was not trained for, such as different wind directions. In Tanaka et al. [12] case, the deep learning method has to be viewed more as a parallel tool to the CFD simulation, useful in the early design process for example. A similar example is also given by the work of Ding et al. [24], which develop data driven regression model for coupled indoor-outdoor flow analysis together with CFD simulations. Eventually, surrogate modeling main advantage resides in the possibility to obtain really fast and inexpensive predictions, otherwise unfeasible with CFD simulations. It also comes with limitations such as being strongly case dependent, without good generalizability, and in need of large training data sets. In most indoor environment studies, only the case related data were used for training. Then the trained ANN was very likely unfeasible for another case that the network was not trained for. Its limited accuracy can become an important factor in practice. Many possibilities of utilization of deep learning models that section 4 will cover are yet to be explored in the built environment, possibly to further increase also the accuracy of the analysis and create more trusty models.

4. Deep learning applied to Fluid Mechanics

The range of applicability of ANNs is in general much richer than what highlighted in section 3. This section aims to inform about possible different techniques and applications of ANNs to drive forward the research in the built environment. Starting from the beginning of the 1900s with the first applications with very shallow ANNs [25,26], the architectures, models and types of interaction are becoming over the year more and more improved and advanced. Fluid mechanics research is not only looking at deep learning methods for computational efficiency but also increased accuracy. Nowadays, fluid mechanics deep learning techniques sees numerous possible applications. Some of them make use of data-driven machine learning models as an aid for augmenting the CFD simulations and their turbulence models. Some others instead present deep learning architectures as surrogate model of fluid dynamics numerical simulation, similarly of what is also done in the built environment. Besides straightforward substitution of CFD with ANN, model order reduction and POD techniques are also reviewed. There are some other applications that use completely different new emerging methods such as super-resolution techniques.

4.1 Turbulence modeling

As remarked already, deep learning techniques can be utilized in conjunction with CFD simulations to increase the accuracy of simulations. Turbulence models introduce a number of constant coefficients varying from model to model, determined experimentally. Therefore, the RANS turbulence models are not universally capable for every flow, but actually depend on the specific flow features. A first obvious way to utilize deep learning algorithm on turbulence models is for *constant tuning*, finding for different flow applications the best values of the coefficients of a particular turbulence model. For example, Yarlanki et al. [27] estimated the temperature in data centers using a tuned standard RANS turbulence model, allowing a reduction of the absolute average error in by 35%. Another example is the work by Luo et al. [28]. The main difference between the two is that Luo et al. [28] provide a **physics informed** neural network by combining the high-fidelity labeled output of DNS simulations with prior knowledge on the mathematical representation of the RANS model. In general, tuning coefficients can increase the accuracy of CFD predictions, but the value of the coefficients of the turbulence models are problem related, with scarce generalizability. Furthermore without proper caution, tuning coefficient techniques could actually introduce more uncertainties to the analysis, compensating for example for experimental errors, inaccurate boundary conditions, etc. Physics informed deep learning modeling can help to contain this problem and increase generalizability so that the same architecture can be applied to different flow fields.

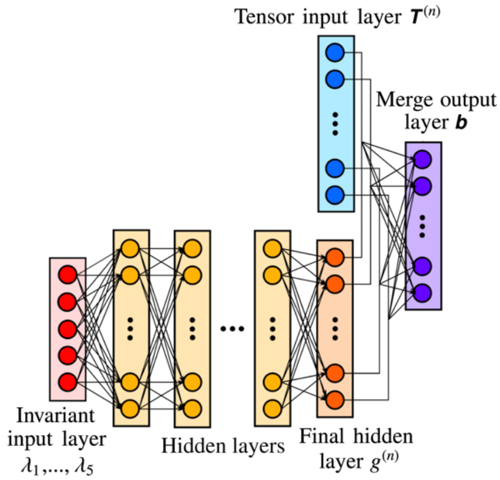

Fig.3 - TBNN architecture used by Ling et al. [37]. It presents a further input layer called Tensor input layer, which makes sure that the ANN embeds the physical property of rotational invariance.

Deep learning algorithm can actually achieve much more when interacting with turbulence modeling. Research is focusing on new ways of enhancing turbulence models by acting directly to the source of uncertainties. An idea is to use deep learning algorithm to build a *representation* of turbulence modeling closure terms. Tracey et al. [29] take a one-equation turbulence model and try to reproduce the same results by replacing its source term of the model with a classic shallow MLP. They established a methodology for future studies where the training data becomes more accurate DNS or well resolved LES simulations. The enhanced model in practice learns the behavior of turbulence leading to better prediction over a wider range of flows. In 2016, Ling et al. [30], for instance, explore the opportunity of using DNS data as labeled output, which accuracy tops RANS's. They act directly on the eddy-viscosity hypothesis, substituting it with an ANN model. The ANN used is a very deep architecture of more than 10 hidden layers, an advanced alternative to MLP, called Tensor Basis Neural Network (TBNN), shown in Figure 3. This custom deep architecture makes use of a tensor basis set to impose within the ANN prior physical knowledge about fluid flows. In particular, it embeds symmetry and physical property of Galilean-rotational invariance, which is ultimately fundamental for accuracy of the CFD solution. Similar applications focusing on augmenting turbulence modeling is for instance the work of Geneva et al. [31] using the same TBNN architecture from Ling et al. [30] coupled with Bayesian statistics. Deep learning can even reveal new hidden correlations where the physical laws are still not known *a priori*. A perfect example of this interaction is given by Font et al. [32] for turbulent flow analysis. They make use of a remarkable custom architecture, being an advanced deep Multiple Input-Multiple Output CNN (MIMO-

CNN). Overall, turbulence model enhancement techniques allow for impressive accuracy improvements, and perhaps most importantly even the discoveries of new equations and correlations about turbulence phenomena that were not known before.

4.2 Surrogate modeling

As shown in section 3 for the built environment, ANNs can also be used to marginally or completely substitute CFD simulations in the analysis of fluid flows. In general, computational efficiency of reduced order based methods can be 1-2 orders higher compared to conventional CFD methods [33], even allowing real-time prediction in some cases. For example, Guo et al. [34] develop a CNN algorithm that performs at least two orders of magnitude faster than equivalent CFD solution with slightly less accurate solution. Fukami et al. [35] instead analyze the feasibility of five different deep learning architecture for aerodynamic design predictions in three different regression problems, including the estimation of force coefficients of wake flows. Sensor measurements were used as labeled output for the network training. The multiple works done primarily by Guastoni et al. [36,37], apply deep learning models to an open channel extremely expensively boundary layer DNS simulation. It is one clear example of the computational efficiency advantage of data driven models surrogate over brutal numerical simulations. In the next sections applications of two methods that are conceptually similar to simple surrogate modeling will be reviewed: POD, and super-resolution.

4.3 POD

Already in 2002, Milano et al. [38] was modeling near wall turbulent flows with POD. POD belongs to the branch of order reduction models and decomposes a physical field into a basis along the principal component analyses, allowing for example to quantify the structure of turbulence through recognized basic patterns [39]. The limitations raised by POD resided in the inherent linearity of the mode decomposition. Milano et al. [38] showed ANNs can actually be viewed as generalization of POD, but with improved architecture consisting of non-linear layers that eliminates the linear limitations of POD. Since the work by Milano et al. [38], the development of model order reduction using POD with ANNs has been uninterrupted. Fresca et al. [40] develop a strategy to make the offline training dramatically faster by performing a prior dimensionality reduction through POD and a pre-training stage where different models are combined to initialize the parameters of the algorithm. Improved ANNs architectures have also been researched over the years. For example, in 2018 Wang et al. [41] applies the LSTM-RNN architecture with POD techniques in the study of ocean currents and flow around cylinder. POD deep learning techniques are eventually an interesting and efficient form of order reduction modeling, which allows much faster predictions while maintaining reasonable accuracy [41].

4.4 Super-resolution

Borrowed from computer vision and image recognition, super-resolution imaging refers to the class of techniques that aims at obtaining a high-resolution image output from a low-resolution image. Deep learning has already been extensively used for super-resolution and lately mainly through CNNs [42], given their predisposition for visual pattern recognition. The same concept could be applied to flow fields by treating them as *images*. Using an offline database of high-resolution snapshot of flow field (for example DNS data) as labeled output, it is possible to give input from low resolution data either from experimental measurements as done by Erichson et al. [43] or from fast and computationally inexpensive simulation. The method consequently reconstructs the turbulent field to high resolution with the ANN. More specifically, Erichson et al. [43] first reconstruct a 2D cylinder with 10 sensors and getting DNS data as high resolution output and subsequently also apply the same architecture to the study of isotropic turbulence. Fukami et al. [14,44] take DNS high-resolution data and purposely down-scale them with a pooling operation to obtain the low-resolution input data. Using two different neural network architecture, one a classic CNN and another improved hybrid ANN algorithm that can handle the multi-scale nature of the flow, Fukami et al. [14,44] successfully reconstruct the same cylinder wake of Erichson et al. [43] and even 2D decaying isotropic turbulence. In all these cases, the model super-resolves the low-resolution field without assuming any *a priori* knowledge of the physics, which demonstrate the strength of data-driven super-resolution techniques. At the same time, the super-resolution opens the possibility to incorporate the knowledge of the physics into the learning process for improved accuracy in future studies. Gao et al. [45] develop a physics-informed deep learning based super resolution solution using a CNN. The aim of a physics-informed algorithm is to guarantee that the super-resolved fields are faithful to the physical laws and principles. As shown, super-resolution techniques eventually offer a new and efficient way to study turbulent flows, with enormous potential especially when coupled with CNNs.

5. Opportunities and challenges in the built environment

Most RANS turbulence models are designed for aeronautics applications with high speed flow, while built environment simulations usually present low velocity fields. The standard coefficients of the models might be inadequate in various scenarios as highlighted by Yarlanki et al. [27]. Tuning coefficients with the use of ANNs is a practical scope that can already decrease error in quantities of interest. By acting on augmenting the turbulence models, further substantial accuracy improvements can be reached. However, the computational efficiency in built environment design problems still needs to be addressed. Coupled deep learning CFD might be unfeasible for some applications, especially when fast predictions are needed, such as in control, design or optimization tasks. On the other hand, surrogate modeling inevitably allows faster computations, but the predictions quality is usually affected. Surrogate modeling is also able to obtain results without any prior physical knowledge about the problem, thanks to a large amount of training data. This is advantageous in some respects, as it is not required previous deep physical knowledge and experience on the problem, but it can be problematic in others. For example, without prior physical knowledge, the trained ANN could provide adequate level of accuracy on the variables trained, but critically non-physical results overall. Physics informed modeling is another possible step into higher quality predictions, which could also increase the generalizability of the model. About the direction of turbulence modeling research, Duraisamy et al. [46] note that one should not throw away the existing knowledgebase in turbulence modeling but rather build on top of it. Some modeling base concepts, such as dimensional analysis and Galilean invariance in turbulence modeling should be preserved in the deep learning architecture. Numerous physics informed modeling have been reviewed in section 4. With the availability of large amount of data, deep learning models are also capable to find hidden correlations or equations that were unknown [46]. This can be extremely important since human preconception and knowledge can harm new discoveries instead of helping achieve them. For example, forcing to fit deep learning models from RANS models when the closure is renowned to fail in multiple cases will certainly not allow great performance improvements. Instead, data driven models might even bypass the traditional ways of hypothesis-driven model creation and instead generate models free from human intuition [46]. A similar philosophy could also be applied in the built environment. The accuracy of simple surrogate modeling and coefficient tuning is highly dependent on the training procedure. The corresponding ANNs show the highest struggle in adapting to cases where the ANN was not trained for, even for simple variables changes as seen in the work by Tanaka et al. [12]. Super-resolution and POD are in general less sensitive in this regard, but they still require a large training data set to achieve good accuracy. Turbulence model augmentations provide a tool to overcome the limitations of standard turbulence models and they should provide the highest generalizability and robustness in applications to different flow scenarios. Finally, the addition of physical information with physics informed modeling can definitely help in improving overall performance of deep learning.

It is important to notice that the power of ANNs in specific tasks reside almost completely in their capacity to interpolate the data. The performance on the test set will be adequate if the test and training set are under similar distribution. A big challenge for deep learning instead resides in the extrapolation process, where ANN can fail even in simple cases [43]. One obvious example of extrapolation task is when the data has the form of a time sequence and the objective of the deep learning algorithm is to inference about future predictions, given historical data as training data (crucial in climate modeling for instance). The deep learning model fails in extrapolating the fields which belong to a different statistical distribution. Therefore, for transient indoor/outdoor airflow, the application of super-resolution requires further investigation. Directly linked to interpolation ability is the renowned ANN hunger for large dataset. In computer vision tasks, the available training data are usually massive. In fluid mechanics, the availability of data is still limited, despite various efforts in the latest years to create fluid mechanics databases of simulations. The research community is still not used to consistently work with open and large shared databases and often prefer to generate simulation data themselves, especially in the built environment, which eventually harm the development of better data driven models. Besides, the scarce availability of large data makes the classic over-fitting problem during the ANN training procedure even more relevant.

6. Conclusions

Thanks to digitization, new data driven tools are starting to make an impact in engineering applications as CFD simulations in the built environment. The objective of this study is to perform a comprehensive review of the current state of the art of the interaction between deep learning models and fluid mechanics simulations, update on the state of the built environment research in the topic, and propose possible advancements in the field. The vast majority of applications in fluid mechanics analysis in the built environment involves deep learning as surrogate modeling for faster predictions, justified by the expensiveness of CFD simulations. Most often, fast predictions come at a cost of degraded accuracy. Fluid mechanics research and applications in general offer inspiration for possible different interaction which could benefit not only prediction speed but also accuracy performance. Above all, physics informed deep learning modeling, turbulence model enhancement with different techniques, and super-resolution techniques are the most promising methods that are largely yet to be explored in the built environment, for both indoor and outdoor simulations. Unfortunately, together with promising advancements, deep learning methods come with challenges to overcome, such as the availability of consistent large flow databases, the extrapolation task problem, over-fitting and others.

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Data sharing not applicable to this article as no datasets were generated or analysed during the current study.