On the hydrodynamics of macroporous structures: Experimental, CFD and artificial neural network analysis

A.J. Otaru, Z.A. Alhulaybi, T.A. Owoseni

ABSTRACT

Porous metallic structures play a critical role in mass and heat transfer processes due to their high surface areas, fixed porosity, and high stiffness – so understanding their fluid flow behaviour is crucial in designing materials that perform efficiently in mass and heat transfer. In view of this, a multi-disciplinary approach is employed to study the hydrodynamics of aluminium foams produced by a liquid melt infiltration technique using experimental, computational fluid dynamics (CFD) modelling and simulation, as well as artificial neural network (ANN) machine learning backpropagation. X-ray computed tomography datasets were used to characterize pore-structure-related properties of replicated materials, followed by three-dimensional advanced imaging of workable representative volume elements. Hydraulic flow information was acquired for the porous matrices using the constant-head permeameter technique. Experiments showed the permeability and Forchheimer coefficient dependence on pore-structure-related properties for fluid-flowing within the pre-Forchheimer and fully developed Forchheimer regimes. Flow permeability of $8.479 \times 10^{-9}$ m$^2$ was highest in the material with the widest mean pore openings (0.212 mm) and lowest (1.291 $\times 10^{-9}$m$^2$) in the material with the narrowest mean pore openings (0.106 mm). Conversely, Forchheimer coefficients were higher for materials with lower porosities and lower for materials with higher porosities. CFD calculations accurately predicted the fluid properties of metallic foams, as well as the influence of intrinsic foam properties on permeability and the Forchheimer coefficient. The ANN model framework was also able to provide valuable information about the hydrodynamics of these materials. Convolution and non-linearity of the ANN model were improved by adding supplementary neurons to the hidden layers allowing deviations within 0.3 and 9.0 percent to be attained.

Introduction

Globally, it is expected that by 2030, all seventeen (17) Sustainable Development Goals will have been met by developing and developed countries. Goal 7 calls for upgrading industrial facilities to supply affordable and clean energy, Goal 9 calls for expanding infrastructure and industry, while Goal 6 calls for ensuring sustainable management of/and ensuring access to clean water. These sustainable development goals entail the exploration and production of new sustainable materials as the world looks to the future. The challenge now facing engineers and scientists around the world is how to design and apply limited materials in a more efficient manner. As one of the most promising materials, exemplified by a wide range of multifunctional capabilities, cellular metallic structures are ideal candidate materials for improving fluid and heat transfer due to their high stiffness, high pore volume, fixed pore network (i.e. porosity does not change near the boundary), embedded tortuosity, high Young modulus, and high surface area [1]. These materials are classified into porous metals (open-celled) and metal foams (closed-celled), respectively, with porosities between 88 – 95% [2] and 60 – 80% [3]. Foams with a higher solid content (thicker ligaments) are closed-celled metal foams, while ones with a lower solid content are porous metal foams. Topology and pore-structural characteristics of these materials are often affected by technological processing (foaming, casting, sintering, etc.) routes and operating conditions [4,5], and they

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can be made from almost all liquid metals or metal powders, including aluminium, copper, nickel, steel, iron, and alloys. During the early 1980s, cellular metals were developed for aerospace applications. Concurrently, these materials are used in a wide range of applications, including thermal hydraulic transport [6–8], fuel cells [9], sound absorbers [10], waste storage filtration and impact reduction [6], air purification technology and environmental reduction [8], and medical devices [7] amongst others, because of improved processing technological routes and lower manufacturing costs.

A fundamental aspect of designing metallic foams for heat and mass transfer applications requires a thorough knowledge of their fluid-structure properties (i.e. permeability \(k_0\) and Form drag \(C_f\)) along with fluid flow regimes and boundaries which directly contribute to the selection of materials for any engineering application. Several studies have been conducted in the literature, including the use of experimental, numerical, and analytical techniques, in order to identify ratiocinate fluid transport properties in metallic foams. For example, the earliest article to discuss water pressure drop in nickel foams with unknown pore density and porosity was first published in [11]. In their study, the friction factor \(f\) (see Eq. (2)) and permeability \(k_0\) were used to treat experimentally measured data and identify the transition from Darcy to inertial. By fitting experimentally measured pressure drop–velocity data into the 2nd order Forchheimer (also known as the Hazen-Dupuit-Darcy) model (Eq. (1)), permeability \(k_0\) and Form drag \(C_f\) were calculated. A unit pressure drop \(\Delta P/L\) is expressed mathematically as a function of Darcian permeability \(k_0\), Form drag \(C_f\), dynamic viscosity \(\mu\), fluid density \(\rho\), Forchheimer coefficient \(C_p\), and superficial fluid velocity \(u_s\). Permeability of porous materials \(k_0\), which represents fluidity, is usually expressed in terms of area (e.g. cm², mm², m², milliDarcy [mD]) and can be calculated using the Henry Darcy equation outlined in Eq. (2) for viscous dominated flows (slow moving fluids).

\[
\Delta P = \frac{\mu u_s}{k_0} + \rho C_f \frac{u_s^2}{k_0} + C \frac{C_f}{k_0} = \frac{C_f}{k_0}
\] (1)

\[
\Delta P = \frac{\mu u_s}{k_0} + \rho C_p = \frac{\rho u_s^2}{\epsilon \mu} D_p
\] (2)

where \(\epsilon\) and \(D_p\) are the material porosity and mean pore diameter.

Dukhan et al. [12] investigated water flows in commercial ERG aluminium foam (6101-T6 alloy) characterized by 20 pores per linear inch (PPI) and 87.7% porosity in a Darcy-turbulent flow regime. The results of 88 large sets of experimental data points showed that permeability and Form drag coefficient varied depending on the flow regime. Friction factor \(f\) and Reynolds number \(Re_{p}\) were estimated using the square root of Darcian permeability as the characteristic linear dimension determining fluid-structure properties. Başçı & Dukhan [2] provided pore-structure-related properties and pressure drop data for 10 and 40 PPI metal foams with comparable porosities of 88.5 percent. In their work [12], they obtained a wide range of flow data that revealed a supportive and dependent relationship between permeability and Form drag on pore-structure-related properties for these materials. The changes with respect to the Reynolds number momentum from Darcy to inertial, which were unity, were deemed most notable. Using the pore-diameter Reynolds number \(Re_p\) as the characteristic linear dimension, the departure from Darcy to inertial was calculated to be between 5 and 10 in [13], whereas Otaru & Samuel [3] determined this value to be between 5.8 and 81.2, based on simulated pressure drop data for Recemat RCM-NCX 1116 porous metal with mean pore-diameter, mean pore-openings, and mean porosity of 2.454 mm, 1.286 mm, and 90 percent, respectively.

Several divergences between fluid-structure properties have also been reported in [11–16] indicating that similar metallic foams may exhibit different flow profiles. In most cases, fluid transport across porous matrices is delineated by the Reynolds number for the determination of these properties. In these studies [11–16], not only Reynolds number, but also pore-morphology, flow direction, sample thickness, and winding pathways (tortuosity) also reportedly played an important role in flow patterns, permeability, and Form drag for metallic foams. However, determining these properties accurately depends profoundly on experimental or predictive pressure/velocity data for a flowing fluid through interstitial pathways. A predictive modelling approach involving both advanced imaging and computational fluid dynamics (CFD) has also been applied to determine fluid-structure properties based on either X-ray computed tomography datasets or virtual images that replicate real-world materials. De Carvalho et al. [17] studied the flow dynamics of high-velocity (2.3 – 26.0 m.s⁻¹) airflow in Inconel 450 and 1200 µm foam samples using high-resolution X-ray computed tomography datasets. Their work showed that permeability and Form drag are dependent on the topology and fluid velocity of the material. Based on a similar pore-level approach, Ranut et al. [18] and Otaru et al. [19] found that the properties of metal foams shaped like a tetrahedron and aluminium foam shaped like a bottleneck have a demonstrable dependency on pore morphology, porosity, pore openings, pore diameters, and superficial fluid velocity.

Despite the numerous applications of pore-level CFD predictive techniques substantiated in the literature [17–22], accurate modelling of experimentally measured pressure-velocity data requires high-resolution images as input datasets, imaging software, and high-performance computers, all of which can be extremely costly. Researchers investigating the transport in metallic foams are now exploring the application of machine learning artificial neural networks (a subset of artificial intelligence [23]) to provide interactions between input and output variables necessary for understanding foam-fluid dynamics. A study by Calati et al. [24] described how aluminium foams enhanced water pool boiling on flat surfaces by using artificial neural networks (ANN). A large set of experimentally measured data containing around 758 data points was acquired, trained, and validated against their experimentally measured Nusselt numbers across 5, 10, and 40 PPI metal foams which were within 90% correlation. A network-based fuzzy inference system (ANFIS) was utilized in [25] to predict the hydrodynamic behaviour and heat transfer of water in metal foam under a constant wall heat flux of 55 kW/m². The results from their study showed that ANFIS achieved the greatest intelligence over all inputs (x-, y-, z-direction) and membership functions considered to give an almost perfect regression correlation. Using experimentally measured data to evaluate the performance of aluminium foam in heat exchangers, Baiocco et al. [26] trained two neural networks (NET1 and NET2) with resilient backpropagation algorithms. The neural network output predicted temperatures for the heat exchanger’s working fluid within nominal experimental scatter while maintaining exchanger input temperature, airflow rate, and material’s pore-structure-related properties as a function of several input variables for the ANN model. Heat and mass transfer was also studied using a feedback ANN in [27] for a porous metal workpiece heated by a fire gun. They found, however, that while the ANN model used in their study had a two-hidden layer structure that learned the correlations between heat flux, radial distance, preheating time, and distance between gun workpieces, their predictions would also need to be validated experimentally. Very few published articles have explored the application of ANNs to understand the hydrodynamics of metal foams and their variable outcomes. Therefore, in this work, a machine learning backpropagation network based on an artificial neural network is applied for the first time to predict pore-diameter-based Reynolds numbers \(Re_p\) associated with water flow within aluminium foams manufactured via negative pressure infiltration. This study was achieved by inverse replication processing of aluminium foams through hydrodynamic measurement of pressure/velocity data for water flow in metal foams using constant head permeameter, CFD analysis of pressure/velocity data using high-resolution X-ray tomography datasets, and development of ANN models to predict output variable functions.
Fig. 1. Photographic images (left) and scanning electron microscopy (SEM) images of porous Al structures made near-spherical salts (1.4–2.0 mm, a) and granulite salts (3.0–4.0 mm, b).

Fig. 2. a. A diagrammatic representation of a constant head permeameter used for pressure drop measurements. b. A plot of the natural log of tortuosity (\(\ln \tau\)) against natural log of porosity (\(\ln \varepsilon\)) using analytically predicted values reported by Dias et al. (2006).
Porous material characterization and flow study: experimental and CFD

Foams made from aluminium (Al) were processed via a negative-pressure replication casting technique similar to that used in [19, 28]. In brief, a liquid melt consisting of 99% aluminium and heated to 800°C (below the melting point of the salts used) was poured into a mould consisting of hollow packed beds of near-spherical hydrosol salt (water softening) characterised by particle sizes ranging from 1.4 to 2.0 mm. After mixing, the liquid melt was allowed to solidify before compaction. Preheating of space holders (salt beads) between 450 and 600°C was done before pouring of the liquid melt to prevent premature solidification. The molten aluminium was injected into packed beds using 0.5 bar infiltration pressure in a 33 mm diameter and 40 mm long vessel. A

Fig. 3. Reconstructed images of aluminium foam [A] showing typical (a) 2D input slice image, (b) watershed segmented pores, (c) 3D representative volume element (RVE) of foam-fluid domain, (d) 3D RVE foam domain (e) 3D RVE fluid domain and (f) 3D RVE meshed fluid domain [2.721 Mcell density].
Gamet-bearing lathe was then used to machine the foam (containing salts) to achieve the desired shape and size to fit into a hollow pipe assembly for subsequent pressure drop experiments. Relative porosity was achieved by dissolving the hollow sphere in a warm water incubation bath at 40°C for three days. As shown in Fig. 1, the synthesized metal matrix is comprised of a skeletal structure (solid) which provides a rigid construct for foam, pores, and interconnected windows. The metallic foam structure was mounted on SEM specimen stub with a carbon-tab for microscopic surface inspection using a Joel WINSEM JSM-6400 scanning microscope. The infiltration pressure of liquid (applied differential pressure), salt shapes and sizes were varied to produce supplementary foam structures using near-spherical, hydrosoft and granulite salts. Fig. 1 shows optical images (left) and secondary (SEM) micrographs (right) for two different aluminium foams fabricated via granulite salts. Fig. 1a shows optical images (left) and secondary (SEM) micrographs (right) for two different aluminium foams fabricated via liquid melt infiltration of hydrosoft (Fig. 1a) and granulite-based salts (Fig. 1b).

A constant head permeameter (Fig. 2a) was constructed to measure the discharge velocity ($v_s$) and head loss ($\Delta H$) of flowing liquid/water through replicated porous aluminium foams at 18 – 20°C. The experiment replicates Darcy’s experiment, which uses water flowing through soils or packed beds owing to the similarities between packed beds and foam structures [29]. The permeameter (Fig. 2a) measures the head loss ($\Delta H$) of water flowing into a tube (water supply) until a steady trickle flows out through the overflow. The internal and external diameters of the pipework used are 37 and 40 mm, respectively. To avoid fluid losses and maintain total control over fluid flow through pores and windows of the foam structures, the pipework’s internal diameter was set to equal that of the foam structures. Additionally, heat shrink tubing was applied to the foam side (diameter 36.8 mm) in contact with the internal wall of the tube to create a seal and maintain a greater coefficient of friction with the foam. A suitably fitted foam sample is critical for minimizing the possibility for errors during fluid permeation through the cross-section of the foam matrix. During each test, water was supplied to the top of the permeameter until liquid was discharged from the overflow at a fixed or constant head. The supply flow rate was controlled to minimize overflow but maintain a constant level. Measurements of mass change over time were used to determine the discharge rate. Tests were repeated by simply changing the height of the head after turning off the supply. Pre-cut pipes of uniform diameter, with different lengths, were used to set up the fixed head ($\Delta H$) which for repeatability was determined from a datum each time and measurements taken for lengths between 0 and 95 mmH2O. The experiment was first conducted on foam A (Fig. 1a) and then repeated for foams with different pore sizes, shapes, connectivity, and interstices. Head losses ($\Delta H$) measured in mmH2O were converted to pressure drop ($\Delta P$) in Pascal. Furthermore, the permeability and Forchheimer coefficient of the macroporous structures were determined through fitting of pressure/velocity data to Eq. (1).

Besides permeability and Forchheimer coefficient, other pore-structure-related parameters were determined prior to the flow measurement study. Among these parameters are porosity, thickness, foam diameter, mean pore openings, mean pore size, specific surface (described as ratio of sample surface area to pore volume [19]), and tortuosity. A Zeiss Xradia Versa XRM-500 X-ray computed tomography (CT) system was used to obtain two-dimensional cross-sectional datasets resulting in approximately 3000 images/slices in tagged image file format (TIFF) for each sample with an equivalent voxel size of 26 μm (Fig. 3a). The 2D datasets were processed via a three-dimensional image processing software (ScanIP module from Synopsys – Simpleware) into a 3D volume and representative 3D volume element (Fig. 3d) by applying various imaging tools (thresholding, filtering, erosion, and dilation) within the ScanIP program. An efficient 3D representative volume element (RVE) was obtained by shrinkage of a large 3D inverted model until the measured porosity differed by only ±3 percent from the experimentally determined nominal porosity possessing a size 3 – 5 times the mean opening diameter of the material. The porosities of the foams were measured using a weighing scale, with known aluminium density of 2710 kg.m$^{-3}$. From the ScanIP, foam porosity, volume, and surface area were measured directly, whereas the average (mean) pore size and the mean pore openings were determined by averaging the watershed segmentation pores (Fig. 3b) and the centrelines of a fluid 3D RVE (representative volume element) by measuring across the pore openings. A measure of tortuosity was calculated by dividing Euclidean distance by boundary distances measured within the ScanIP. The values of tortuosity obtained for the five foams were compared to an analytical tortuosity model validated in [30]. According to Dias et al. [30], ($\tau$) dynamic tortuosity of porous materials is exponentially dependent on the porosity ($\varepsilon$) of the material, the shape factor, ($C_\text{s}$) and the tortuosity factor or Bruggeman’s correlation ($n$), mathematically expressed as $\tau = C_\text{s} \varepsilon^{-n}$. Fig. 2b shows the natural log of dynamic tortuosity for each sample against the natural log of porosity which shows a linear inverse

![Graph](image)
relationship with a shape factor of 1.40 and Bruggeman's correlation of 0.58. This predicted tortuosity factor falls within the lower (0.4) and upper (0.6) bounds reported in [30] for most metallic foams, and 0.5 for packed spheres.

A mesh structure capable of fast and accurate convergence was applied to the image-processed 3D RVE fluid domain (Fig. 3e) within the +FE module of Synopsys – Simpleware. A linear tetrahedral mesh structure (LTM) with a minimum and maximum edge length of 3x and 7x voxel dimension of the images was applied to the RVE fluid domain with a growth rate of 1.3. For all five foams, this approach yields optimum mesh density (2.6–3.3 Mcells) that captures over 98% of the gradient of velocity across their interstices (see Fig. 3f). This cell density range was observed due to foam materials’ topology and solid content. The density of cells in RVE-derived fluid domains with larger bulk volumes (less material content) was higher, while the density was lower for materials with more solid content. Below this range of cell densities, the velocity gradient captured was poor compared to experimental data. With a velocity inlet, zero pressure outlet, and symmetrical boundary conditions, the Navier – Stokes equation (Eq. (3)) was solved for the meshed structure. The equation was chosen due to its numerous applicability for accurately predicting laminar fluid flow regimes [3,5] and, for this study, a maximum pore–diameter Reynolds number of 53.156 was obtained, which falls within the laminar regime for fluid flows in porous media. Resolving each velocity input discretely for the range of velocities required around two to three hours on a 64 GB RAM/3.7 GHz processor. Thus, the degree of pore openings and contact formation by connecting pores determines how much fluid is permeated across the interstices of aluminium foams. In contrast, the Forchheimer coefficient was highest (40.398) for foam C (very low porosity) and lowest (2.021) for foam D, which had the highest porosity. This agrees with work reported in [3], which showed an exponential inverse relationship between porosity and inertial coefficient in porous metallic foams.

According to Fig. 4a, water flow across porous metallic structures increases quadratically with increasing head losses (pressure drop). The flow restriction is less for materials with larger-sized pores and higher porosity whilst highest for materials with smaller-sized pores and lower porosities. Using Eq. (2), it can be determined that the pore-diameter Reynolds number (Reₚ) for these foams’ ranges between 0.99 and 53.15. For foam C, range between 0.99 to 11.32 is determined, while for foam E, a much wider mean pore size and pore volume fraction results in range between 5.13 and 53.15. Correlating pressure/velocity data with similar experimental studies reported in [12,32] reveals the regime of manifestation of flowing fluid in these porous materials. Firstly, Lage et al. [32] classified flow regimes in porous media into Darcy, pre-Forchheimer, Forchheimer, post-Forchheimer, and turbulence. The authors determined that pore-diameter-based Reynolds numbers between 0 and 1 corresponded to Darcy flow, while Reynolds numbers between 1 and 10 represented pre-Forchheimer flow (i.e. transition from Darcy to inertial). For fully developed inertial flow, pore-diameter-based Reynolds numbers ranged between 10 and 150, while values above 300 were reported [32] for turbulent flow. Independently, Dukhan et al. [12] determined that water flow velocities between 4 and 7 mm.s⁻¹ and

### Table 1

Tabular representation of pore-structure-related and flow information data.

<table>
<thead>
<tr>
<th>Materials</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foam weight (g)</td>
<td>21.870</td>
<td>32.900</td>
<td>28.470</td>
<td>19.190</td>
<td>20.880</td>
</tr>
<tr>
<td>Salt type</td>
<td>Hydrosoft</td>
<td>Granulite</td>
<td>Spherical</td>
<td>Hydrosol</td>
<td>Hydrosol</td>
</tr>
<tr>
<td>Sample diameter, S₀ [mm]</td>
<td>36.800</td>
<td>36.800</td>
<td>36.800</td>
<td>36.800</td>
<td>36.800</td>
</tr>
<tr>
<td>Porosity, ε [-]</td>
<td>0.746</td>
<td>0.618</td>
<td>0.671</td>
<td>0.777</td>
<td>0.740</td>
</tr>
<tr>
<td>Salt size range, Sₙ [mm]</td>
<td>1.4 - 2.0</td>
<td>3.0 - 4.0</td>
<td>1.4 - 2.0</td>
<td>0.5 - 4.0</td>
<td>2.0 - 2.5</td>
</tr>
<tr>
<td>Foam length, L [mm]</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>Mean pore size, Dp [mm]</td>
<td>1.604</td>
<td>3.49</td>
<td>1.630</td>
<td>1.659</td>
<td>2.28</td>
</tr>
<tr>
<td>Mean pore opening, Dw [mm]</td>
<td>0.170</td>
<td>0.130</td>
<td>0.106</td>
<td>0.212</td>
<td>0.154</td>
</tr>
<tr>
<td>Tortuosity, T [-]</td>
<td>1.660</td>
<td>1.842</td>
<td>1.770</td>
<td>1.612</td>
<td>1.669</td>
</tr>
<tr>
<td>Specific surface, Sₚ/Vₚ [mm⁻¹]</td>
<td>4.34</td>
<td>3.74</td>
<td>3.83</td>
<td>4.59</td>
<td>3.50</td>
</tr>
<tr>
<td>Infiltration pressure, P [bar]</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>1.0</td>
</tr>
<tr>
<td>Fluid Density, ρ [Kg/m³]</td>
<td>997.78</td>
<td>997.78</td>
<td>997.78</td>
<td>997.78</td>
<td>997.78</td>
</tr>
<tr>
<td>Foam-Fluid (EXPT) Permeability, k₀/10⁻⁴ [m²]</td>
<td>5.336</td>
<td>1.701</td>
<td>1.291</td>
<td>8.479</td>
<td>4.869</td>
</tr>
<tr>
<td>Foam-Fluid (CFD) Permeability, k₀/10⁻⁴ [m²]</td>
<td>2.606</td>
<td>3.872</td>
<td>40.398</td>
<td>2.021</td>
<td>3.725</td>
</tr>
<tr>
<td>Forchheimer coefficient, Cₜ [-]</td>
<td>2.836</td>
<td>33.198</td>
<td>38.862</td>
<td>1.805</td>
<td>4.092</td>
</tr>
</tbody>
</table>

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between 7 and 20 mm.s\(^{-1}\) corresponded to fully developed Darcy regimes and transition to inertial regimes, respectively. Water velocities between 20 and 140 mm.s\(^{-1}\) and beyond 200 mm.s\(^{-1}\) were found to exhibit fully developed inertial (Forchheimer) and turbulence processes, respectively. These authors’ findings suggest that Fig. 4 illustrates flow information that lies in between pre-Forchheimer (the transition from Darcy to inertial) and fully developed Forchheimer regimes. At the Darcy regime, Dybbs and Edward \[31\] found that viscous flow dominates for porous media whose flow permeability is strongly influenced by the structure’s topography. As illustrated in Fig. 4b, Dukhan et al. \[12\] showed that at Forchheimer fluid flow regimes, reduced pressure drop is linearly related to superficial inlet fluid flow velocity, which is directly connected to Reynolds number as mathematically expressed in Eq. (2). In this Forchheimer regime of fluid flow, boundary layers begin to form near pore walls, resulting in inertial forces that are dependent on pore volume fractions (porosity) and specific surfaces. Therefore, Fig. 4 demonstrates that fluid velocity appears high in this regime as kinetic energy is dissipated between moving fluid and pore walls as the fluid propagates through successive cells, pore openings and constricted ligaments.

The pore-level (or pore-scale) computational model used in this study to predict pressure drop across the interstices of materials usually relies on structured-derived representative volume elements (RVEs). Modelling and experimental results presented in Fig. 4 may differ somewhat due to differences in the size of the RVE \[19,33\], mesh structure dependence \[17,18\], and more importantly, the accurate

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**Fig. 5.** Experimental and CFD modelled plots of unit pressure drop [Pa.m\(^{-1}\)] against superficial fluid velocity [mm.s\(^{-1}\)] for different samples of porous metallic structures. Right of the plot: (a) 3D CFD velocity flow distribution for a 5.11 m.s\(^{-1}\) input flow velocity for sample A, (b) 3D CFD pressure distribution for a 5.11 m.s\(^{-1}\) input flow velocity for sample A, (c) 3D CFD velocity flow distribution for a 27.75 m.s\(^{-1}\) input flow velocity for sample A, and (d) 3D CFD pressure distribution for a 27.751 m.s\(^{-1}\) input flow velocity for sample A.
selection of physics and boundary conditions within the computational domains \cite{19}. In terms of predictions, the workable RVE flow dimension of 3 to 5 times the mean pore diameter was more accurate than a shorter thickness. For short thickness samples, porosities differed significantly from the experimental values of nominal porosities, supporting the continuum hypothesis in fluid mechanics of having a representative fluid element to describe their behaviour. Even when the RVE size and meshing are justified, CFD prediction of flow properties is accurate only when the appropriate boundary conditions and physics are deployed. According to the experimental description in this study, the manifestation of fluid flow across these porous matrixes fall into two regimes: the pre-Forchheimer regime and the fully developed Forchheimer regime (both are laminar flowing regimes \cite{12}). Due to their numerical applicability \cite{3, 19} for predicting flowing fluids in the laminar regime, the Navier–Stokes (N–S) equation was employed as the physics (Eq. (3)).

Fig. 5 shows a plot of unit pressure drop \([\text{Pa.m}^{-1}]\) against superficial inlet fluid velocity \([\text{mm.s}^{-1}]\) for foams A, B, and E (see Table 1). Three-dimensional streamline/arrow plots showing velocity and pressure dispositions across foam matrix interstices are shown on the right hand side. CFD-predicted data differed only negligibly from experimental data (2.3 percent) for foam A but most significantly (4.3 percent) for foam E. Table 1 shows calculated values of permeability \(k_0\) and inertial or Forchheimer coefficient \(C_F\) for these structures by means of CFD data. Clearly, CFD values closely match experimental values for these flow properties, thus indicating that a relatively small sample of 3D RVE (3 – 5x mean pore openings) is sufficient for comparative accurate prediction of flow information. Slight discrepancies between CFD predictions and experiments can be attributed to the non-homogenous nature of the foam samples (Fig. 1) caused by a smaller number of half-size salts present in the packed beds during casting. Thresholding two-dimensional images derived from X-ray CT can be very time-consuming and complex if there are half-sized pores in the images, which can affect the value of nominal porosity in 3D models (derived from ScanIP). The images in Fig. 5 illustrate how flowing fluids flow from left to right and that their intensity decreases as they flow from the inlet to the outlet of the material, as indicated by arrows. Observations revealed that intensities were higher within pore openings (“windows”) in foam structures - highest for foam C, which had the narrowest mean pore opening (0.106 mm), and lowest for foam A, which had the widest mean pore openings (0.172 mm). Foam-fluid properties are therefore driven by pore openings in materials as well as other pore-structure-related properties.

Backpropagation artificial neural network analysis of experimental data

To predict the experimental output described in Fig. 4, any artificial neural network (ANN) will need to interact with several inputs \(x_1\) and outputs \(y\) signals with synaptic weights \(w_i\) and biases \(b_i\) as described in \cite{34}. Machine learning artificial neural network setup usually requires data between 0 and 1 as output signals \cite{24}. Accordingly, Fig. 6 presents an ANN model construct with the ratio of pore-diameter Reynolds number to maximum pore-diameter Reynolds number (53.16) used as the predictive output signal \(a_6\). Similarly, all input signals \(x_1, x_2, \text{ and } x_3\) were set up from 0 to 1 – making them dimensionless. As the experimental output and input signals are not linear, hidden nodes (neurons) are advisable \cite{24–27} as in the ANN model illustrated in Fig. 6. According to Sirinar et al. \cite{34}, the model’s convolution and non-linearity can be improved by adding more hidden layers (i.e. by simply adding more neurons). Therefore, the key objective is to improve the predictive output signal so that it closely matches experimental measurements by simply training the ANN model setup (Fig. 6) whether there are extra hidden neurons (deep neural network [DNN]) or not (single neural network [SNN]). Thus, the ANN model setup in Fig. 6 has

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**Fig. 6.** DNN with three input neurons, two hidden neurons, and one output neuron.
been mathematically described, and a detailed mathematical model can be found in the supplementary data.

In Fig. 7, the experimental and ANN predictions of dimensionless reduced pressure drop ($P/P_{\text{max}}$) versus reduced pore-diameter-based Reynolds numbers ($\text{Rep}/\text{Rep}_{\text{max}}$) are plotted for all the foams considered in this study. The data in Table 2 shows the initial, midway and final values for the weights ($w_i$), biases ($b_i$), total cost ($\sum C$), and linearity rates used to train the ANN model presented in Fig. 6. To train the ANN model, Microsoft Excel Spreadsheet and its Visual Basic Application (MS Excel VBA) were used. Linearity rates were adjusted, and the cost function was reduced to near zero, which was crucial to its conclusion.

As an important footnote, the starting or initial values are the first arbitrary guesses used in training the model to determine subsequent values for weights and biases. During training of the ANN network, numerical values were obtained between the initial and midway or midway and final arbitrary values with a cost of 0.9648 for the final trained data. Figs. 7a and 7b show experimental and ANN modelled data for foams A and B based on initial, midway and final values while Fig. 7c shows experimental and ANN modelled data for foams C, D and E. According to Figs. 7a and 7b, the ANN models produced output signals that were constant (i.e. 0.94) but deviated significantly from the experimental ($\text{Rep}/\text{Rep}_{\text{max}}$) irrespective of variations in head losses. However,
observable improvements in predictive values closer to experimental were attained as the ANN network continued to be trained, learning successively through systematic processing resulting in a better output signal that matched more closely to the experimental.

As shown in Table 2, the linearity rate was changed to improve the output signal. In the training of the model, for example, the difference between preceding and succeeding numerical values could be observed to be insignificant at some point. A reduction in linearity rate (between preceding and succeeding numerical values) could be observed in the output signal. In the training of the model, for example, the difference between experimental and the ANN-predicted output signals were very slow, and resolving the total cost closer to zero may take upwards of several months despite running continuously within VBA codes written in MS Excel. Therefore, the ANN setup in Fig 6 was improved by adding more hidden neurons and layers. In accordance with [34], neurons were added to the hidden-layers of the ANN model to improve the output signals. As a result, Fig 7 shows a three-layer deep neural network (DNN) with two hidden neurons and a layer added, connected by twelve (12) synaptic weights and five (5) biases for improvement.

![Deep-layer neural network (DNN): three input, two-additional hidden neurons and one output.](image)

Table 3 lists the characteristic parameters for the three-layer ANN model showing typical values for arbitrary constants (i.e. synaptic weights \([w]_i\), and biases \([b]_j\)), linearity rate \((k)_L\) and total cost \((\sum C)\).
Based on the description in Table 2, the initial guess for the three-layer network (Fig. 8) is 0.1 and linearity rate is 5, resulting in a total cost ($\sum C$) of 4.496, that is closer to zero than the initial total cost of the two-layer ANN model (i.e. $\sum C \sim 15.8541$, see Table 2). Before the network’s training was stopped and values taken, the value decreased to 0.152 using a linearity rate of 0.01. The final value of 0.152 may grow closer to zero if further training is conducted over a longer period of time. As shown in Fig. 9, several thousand preceding and succeeding values were calculated during training of the network until final values were obtained, improving the output signal to match experimental values more closely. In comparison with Table 2, more synaptic weights ($w_1 - w_{12}$) and biases ($b_1 - b_3$) of the network were initially estimated and computed during training of the three-layer ANN model (Fig. 8) and this can be attributed to the addition of supplementary hidden neurons to the model. Moreover, Table 3 shows that the final trained value of synaptic weight $w_2$ (4.673) is much higher than the weight, $w_1$, (-19.892) and $w_3$, (0.669), indicating that the variation in pore-diameter openings of porous materials (Input 2) greatly influences the hidden output 4. A similar observation was made for hidden output 5, revealing a higher contribution from the porosity (Input 1) of the materials. Even though hidden output 4 is driven by mean pore openings, this output contributes more to the viscous regime of the structure (permeability) than output 5, which is driven by the materials’ porosity and contributes to the flow’s inertial regime (Forchheimer coefficients). These findings confirm the widely accepted belief [3,5,19–22] that the porosity and pore-diameter openings of metal foams are crucial for achieving...
optimum fluid flow performance.

Conclusion

In this study, liquid melts are infiltrated into convergent gaps created by packed beds of sodium chloride salts to create porous aluminium foams. Prior to a hydrodynamic study, samples were characterized for their porous structure from X-ray computed tomography datasets followed by three-dimensional advanced image analysis. Experimental and computational fluid dynamic simulations were carried out on porous metallic foams with varying pore sizes, pore openings, and interstices. The constant head permeameter technique used in this study provided fluid flow information for these materials – typically, their permeability, Forchheimer coefficient and fluid flow that fall into pre-Forchheimer and fully developed Forchheimer regimes. While both permeability and Forchheimer coefficients depend on pore-structure-related properties, the former dominates at low velocity, while the latter dominates at high velocity. CFD results were in reasonable agreement with experiments, suggesting that pore openings contribute significantly to fluid flow regimes within the foam interstices which further confirms the viability of the pore-scale technique in providing useful information for such complex materials.

Machine learning backpropagation artificial neural networks were used to establish the relationship between pore-structure-related properties and fluid flow information. By using ANNs, input and output signals are related via a network of hidden neurons to improve convoluted nonlinearity of the data. Predictions using this approach were within experimental scatter (deviations between 0.3 and 9 percent) after subsequent training of the ANN model. A three-layer ANN model was observed to be better at predicting the results than a two-layer model. Pore openings and porosity of the foams were deemed contributing factors to fluid flow properties and were found to influence the permeability (viscous dominance) and Forchheimer coefficient (inertial dominance) for the foam’s hydrodynamics. Based on this approach, the addition of high hidden neurons improves predictive output signals and reduces training time, resulting in improved output signals for metallic foam materials.

CRediT authorship contribution statement

A.J. Otaru: Software, Conceptualization, Methodology, Software, Writing – original draft, Data curation, Investigation, Supervision. Z.A. Alhulaybi: Visualization, Validation, Formal analysis, Resources. T.A. Owoseni: Writing – review & editing, Project administration, Formal analysis.

Declaration of Competing Interest

This work is free of conflicts of interest.

Data availability

Data will be made available on request.

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Supplementary materials


References