

Review

Continuum Porous-Medium CFD Modelling of Rock-Bed Thermal Energy Storage Systems: A Review of Pressure-Drop and Interphase Heat-Transfer Correlations

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Abstract

Rock-bed thermal energy storage (RTES) systems are attracting growing interest as low-cost, robust, and scalable sensible heat storage solutions for applications ranging from low-temperature building and greenhouse heating to medium- and high-temperature solar or waste-heat recovery systems. However, their thermo-hydraulic performance is strongly influenced by the complex interactions among heat-transfer-fluid flow, irregular rock morphology, porosity, pressure drop, interphase heat transfer, and transient thermal-front development. This review provides a focused evaluation of computational fluid dynamics (CFD) modelling strategies for packed beds of rocks, with particular attention to continuum porous-medium approaches and the closure correlations required for reliable simulation. First, the distinction between pore-scale and volume-averaged continuum modelling is discussed in terms of the trade-off between physical resolution and computational feasibility. The main pressure-drop and friction-factor correlations are then reviewed and compared, including classical packed-bed models and rock-bed-specific formulations. It is shown that hydraulic-resistance predictions are highly sensitive to particle shape, surface roughness, porosity, the bed-to-particle diameter ratio, and packing arrangement. Particle-fluid heat-transfer correlations are also examined and, when possible, converted into a consistent particle Nusselt-number form to enable direct comparison. Particular attention is given to generalized correlations, dispersion-corrected models, and air-rock-bed correlations applicable to thermal storage systems. Finally, a methodological framework for modelling RTES systems using local thermal equilibrium (LTE) and local thermal non-equilibrium (LTNE) formulations is proposed. Dimensionless criteria, including the interphase thermal coupling number and particle *Biot* number, are introduced to support the selection between LTE and LTNE formulations. The selection of pressure-drop/friction-factor and solid-fluid heat-transfer/particle Nusselt-number correlations should be based on the similarity between the original experimental conditions and the target RTES system, and system-specific validation is recommended whenever possible.



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1. Introduction

The global energy industry is rapidly evolving to reduce greenhouse gas emissions, enhance energy security, and increase the share of renewable energy in power and heat-

ing systems. This transition is largely driven by solar and wind power, owing to their abundance, declining costs, and low operational environmental impact. However, their intermittent and weather-dependent nature creates a mismatch between energy supply and demand. For example, solar energy is typically available during the day, whereas heating demand in buildings, greenhouses, and industrial applications may peak in the evening or at night. Similarly, wind power generation can fluctuate significantly over both short- and long-term time scales. This temporal mismatch restricts the direct utilization of renewable energy and increases the need for reliable storage technologies [1].

Hence, energy storage systems are required to enhance the flexibility, stability, and efficiency of renewable-based energy systems. Although electrical storage technologies, such as batteries, are widely used for power management, a significant share of end-use energy demand is for heat. According to the *International Energy Agency (IEA)*, heat accounts for nearly half of global final energy consumption and a large share of energy-related CO₂ emissions [2]. Therefore, storing energy directly in thermal form can be more practical and cost-effective than converting heat to electricity and then back to heat [3]. Thermal energy storage (TES) enables this process by storing excess thermal energy when it is available and releasing it when demand increases [4,5].

TES technologies can play several important roles in future energy systems. They can shift thermal loads from peak to off-peak periods, lessen dependence on backup systems powered by fossil fuels, improve the utilization of solar thermal and photovoltaic/thermal systems, and support electrification strategies by enabling heat pumps or electric heaters to run when the cost of power is cheap or there is great availability of renewable energy. TES is particularly important in cold climates, where heating demand is high and often does not coincide with renewable energy production. Thus, for applications such as buildings and greenhouses, TES can increase operational flexibility while reducing energy costs and carbon emissions [6,7].

Sensible heat storage is the simplest and most mature among the various TES methods. In sensible TES, energy is stored by increasing the temperature of a storage medium without undergoing a phase change or a chemical reaction [8]. Water, concrete, ceramics, and rocks are among the materials that have been widely studied for this purpose. RTES is particularly attractive because natural rocks are inexpensive, widely available, chemically stable, non-toxic, and suitable for repeated thermal cycling. When arranged in a packed bed, rocks provide a large surface area for convective heat transfer with a flowing heat transfer fluid (HTF), commonly air [9]. These characteristics make rock-bed thermal energy storage (RTES) systems promising candidates for low- and high-temperature applications, including solar heating, waste heat recovery, greenhouse heating, and building energy management [10].

However, the performance of RTES systems is strongly dependent on the coupled fluid dynamics and thermal transfer inside the porous matrix. During charging, the HTF transports thermal energy into the bed, where it is transferred to the solid particles [11]. During discharging, the process is reversed, and the stored heat is extracted from the rock matrix. The efficiency of this process is affected by several factors, including bed geometry, particle size, porosity, permeability, tortuosity, flow rate, rock thermophysical properties, pressure drop, heat losses, and the degree of thermal stratification. Therefore, accurate modeling of fluid flow and heat transfer in RTES is crucial for designing efficient systems, optimizing operating conditions, and scaling up laboratory concepts to practical applications [12].

Practical RTES systems differ from ideal packed beds because irregular, polydisperse rock particles can generate nonuniform porosity, tortuous flow paths, local channeling, wall effects, and packing-dependent hydraulic resistance, underscoring the need for appropriate

pressure-drop and heat-transfer closure correlations. Moreover, severe cyclic thermal shocks can modify crack and pore structures in granite, highlighting the broader importance of rock morphology and cyclic thermal response in rock-based thermal storage systems [13].

In this context, continuum modeling offers an effective approach for predicting the thermo-hydraulic behavior of RTES systems by treating the packed bed as an equivalent porous medium rather than resolving the complex pore-scale geometry of individual particles. This method is particularly useful for engineering-scale simulations, where resolving the full pore structure of a rock bed would be computationally expensive, especially under transient charging and discharging conditions. Using volume-averaged governing equations, the impact of the porous structure on heat transfer and fluid flow can be represented by macroscopic parameters such as porosity, permeability, inertial resistance, effective thermal conductivity, and interfacial heat-transfer coefficients. Thus, continuum models can be used to assess pressure drop, temperature distribution, thermal-front propagation, stratification, and overall charging/discharging performance at a reasonable computational cost. Depending on the thermal coupling between the fluid and solid phases, these models are usually developed either under the assumption of local thermal equilibrium (LTE), where a single temperature field is used for both phases, or local thermal non-equilibrium (LTNE), where separate energy equations are solved for the fluid and solid phases. Hence, continuum modeling serves as a useful bridge between detailed pore-scale physics and system-level design, enabling parametric studies, optimization, and scale-up of RTES systems.

The present review has a narrower and more focused objective than previous reviews and technical notes. Hoffmann et al. [14] recently discussed CFD challenges in rock-packed beds from the perspective of the volume-averaging method, with emphasis on irregular particle shapes, *Reynolds*-number definitions, pressure-drop and heat-transfer coefficient estimation, and effective thermal conductivity modelling. Other review papers have addressed packed-bed solar energy storage systems, experience feedback, numerical modelling of packed-bed TES, and general modelling approaches for packed-bed thermal storage systems [7,11,12]. In contrast, the novelty of the present review lies in its focused treatment of the closure relations required for continuum or volume-averaged CFD simulations of RTES systems. Particular attention is given to particle diameter definitions, porosity, hydraulic resistance/friction-factor correlations, particle–fluid heat-transfer correlations, and the implications of LTE and LTNE formulations. A key contribution of this work is that the pressure-drop correlations are organized and, where possible, compared in a consistent packed-bed friction-factor form. In contrast, the heat-transfer correlations are discussed using a comparable particle Nusselt-number framework. This enables the influence of particle morphology, roughness, porosity, *Reynolds*-number range, particle diameter definition, and rock-bed-specific operating conditions to be more clearly interpreted. In addition, the reviewed closure correlations are explicitly linked to porous-media CFD implementation, including the conversion of pressure-drop models into momentum-source terms and the use of interphase heat-transfer correlations in LTNE formulations. Finally, the review proposes a practical LTE/LTNE model-selection framework to support continuum CFD modelling of RTES systems. Thus, the main contribution of this paper is not only the compilation of existing correlations, but also the interpretation of their applicability, limitations, and implementation requirements for reliable continuum-scale modelling of irregular rock-bed thermal energy storage systems.

The literature was identified through a systematic search of peer-reviewed journal articles, conference papers, technical notes, and relevant books in databases including *ScienceDirect*, *Scopus*, *Web of Science*, *Google Scholar*, *SpringerLink*, and *MDPI*. The search covered both classical packed-bed studies and recent publications up to 2025. The keyword combi-

nations included “rock-bed thermal energy storage,” “packed-bed thermal storage,” “porous-media CFD,” “volume averaging method,” “LTE,” “LTNE,” “pressure-drop correlation,” “friction factor,” “Ergun equation,” “particle Nusselt number,” “interphase heat-transfer coefficient,” “Sauter mean diameter,” “irregular particles,” and “crushed-rock packed bed.” Papers were included if they proposed, compared, or applied models relevant to the continuum simulation of packed rock beds, particularly those reporting hydraulic resistance, heat-transfer closure laws, effective thermal properties, particle diameter definitions, or TES charge/discharge modeling. Studies were excluded if they focused solely on unrelated chemical reactors, structured catalysts, fluidized beds, or packed beds, with no transferable information for rock-based sensible TES. Priority was given to sources that proposed original correlations, reported clear validity ranges, or addressed irregular particles and rock-bed applications, while widely used classical correlations were retained as benchmark models.

2. Hydraulic Resistance in RTES Systems

Hydraulic resistance is a major thermo-hydraulic property of RTES systems, as it controls the pressure drop required to force the heat-transfer fluid through the porous bed. Flow through the tortuous void network of rock or particle-packed beds directly influences the mechanical power required by the blower or fan. Since pressure losses affect operating costs, system feasibility, and achievable flow rates, recent studies and reviews of packed-bed TES systems treat hydraulic resistance as a primary design parameter rather than a secondary hydraulic feature [15–18].

Accurate prediction of hydraulic resistance is very important in system design, since it influences blower selection, flow-rate capability, auxiliary energy consumption, and the usable thermal performance of the storage unit. For crushed-rock RTES systems, pressure-drop prediction is particularly important for economic feasibility, as both blower sizing and practical operating conditions depend strongly on the estimated resistance. More generally, studies on packed beds show that particle size and shape, bed dimensions, packing arrangement, and particle orientation significantly affect pressure loss, indicating that inaccurate resistance estimates can directly lead to poor design decisions [19–21].

The design of RTES systems involves a trade-off between thermal and hydraulic performance. Smaller particles generally increase the specific surface area and enhance convective heat transfer between the fluid and solid phases. However, they also reduce permeability and increase pressure drop, thereby increasing the fan or blower’s power requirement. This compromise is particularly relevant in RTES systems, where the improved thermal exchange achieved with smaller rocks may be offset by higher auxiliary power consumption due to increased hydraulic resistance [15–18].

The need for accurate hydraulic-resistance prediction becomes even more important when continuum or porous-medium CFD models are used. In these models, the pore geometry is not explicitly resolved; therefore, the effect of the solid matrix on the flow field must be represented through empirical or semi-empirical closure relations, often based on *Ergun*-type formulations. However, recent analyses of crushed-rock RTES systems highlighted that the conventional *Ergun* equation was originally developed under simplified conditions and may not fully capture the behavior of non-spherical, angular, rough, or polydisperse particles. In some densely packed RTES cases, deviations of approximately 10–30% have been reported, emphasizing the limitations of using a single equivalent particle diameter or scalar resistance coefficient to represent natural rock media [16,18,22]. Thus, precise prediction of hydraulic resistance is critical, as it governs auxiliary power consumption, constrains the practical operating window, influences thermo-hydraulic optimization, and is essential to the validity of continuum-scale CFD simulations. This issue is particularly important for packed beds of natural or crushed rocks, for which no single correlation

has been shown to accurately predict pressure loss under all geometrical, material, and operating conditions.

Following the discussion on the importance of accurate hydraulic-resistance prediction in RTES systems, it is useful to clarify how this hydraulic behavior is represented in the literature. In the RTES, hydraulic resistance is commonly quantified by the total pressure loss, Δp , the axial pressure gradient, $\Delta p/L_{PB}$, or the dimensionless friction factor, f , where $\Delta p = p_i - p_o$, with p_i and p_o as the inlet and outlet pressures, respectively, and L_{PB} the bed length. The majority of packed-bed hydraulic correlations are expressed in terms of pressure loss per unit length.

A dimensionless representation is often preferred when comparing data obtained under different operating and geometrical conditions. One commonly used packed-bed friction factor is expressed as follows [23–25]:

$$f = \frac{\Delta p}{L_{PB}} \frac{D_P}{\rho_f \times u_{Superficial}^2} \frac{\varepsilon^3}{1 - \varepsilon} \quad (1)$$

$$u_{Superficial} = \frac{\dot{m}}{\rho_f \times A_C} \quad (2)$$

where D_P is the particle diameter, ρ_f is the fluid density, $u_{Superficial}$ is the superficial velocity, and ε is the bed porosity. Also, A_C and $\dot{m}$ denote the empty-bed cross-sectional area normal to the flow direction and the mass flow rate, respectively.

The flow regime is commonly characterized using the packed-bed particle *Reynolds* number (standard version based on superficial velocity) [23–25]:

$$Re_P = \frac{\rho_f \times u_{Superficial} \times D_P}{\mu_f \times (1 - \varepsilon)} \quad (3)$$

where μ_f is the dynamic viscosity of the fluid. It should be noted that alternative definitions of both f and Re_P have been reported in the literature, depending on the selected characteristic particle diameter and porosity correction. For example, a modified packed-bed *Reynolds* number is sometimes defined as $Re_{P,m} = (\rho_f \times u_{Superficial} \times D_P) / \mu_f$.

The relationship between pressure gradient and friction factor is illustrated by the classical *Ergun* equation, which remains one of the most widely used hydraulic correlations for packed beds [23–25]. In its conventional form, the *Ergun* equation is written as follows:

$$\frac{\Delta p}{L_{PB}} = \frac{150 \times \mu_f \times (1 - \varepsilon)^2}{\varepsilon^3 \times D_P^2} u_{Superficial} + \frac{1.75 \times \rho_f \times (1 - \varepsilon)}{\varepsilon^3 \times D_P} u_{Superficial}^2 \quad (4)$$

The first term on the right-hand side represents the viscous contribution to hydraulic resistance, whereas the second term accounts for inertial effects. Using the definitions of f and Re_P given above, the *Ergun* equation can be recast in dimensionless form as follows:

$$f = \frac{150 \times (1 - \varepsilon)}{Re_P} + 1.75 \quad (5)$$

This compact expression describes the transition from viscous-dominated to inertia-dominated flow and serves as the basis for many subsequent packed-bed pressure-drop correlations.

Despite its apparent simplicity, comparing published correlations directly is not always straightforward. Different studies have adopted different definitions of equivalent particle diameter, including nominal diameter, equivalent-volume diameter (D_v or D_{eq} , $D_v = ((6V_P)/\pi)^{1/3}$), surface-volume diameter ($D_{sv} = (6V_P)/A_P$, ratio of particle volume to

surface area), and *Sauter* mean diameter. The nominal diameter is usually based on sieve size or direct measurement and is therefore simple but shape-dependent. The equivalent-volume diameter represents the diameter of a sphere with the same particle volume, while the surface-volume diameter accounts for both particle volume and external surface area. For packed beds with particle-size distributions, the *Sauter* mean diameter, $D_{32} = 6\sum V_{p,i}/\sum A_{p,i}$, is often more appropriate because interphase heat transfer occurs at the solid–fluid interface and is therefore strongly related to the available surface area per unit volume. The diameter of a sphere with the same volume-to-surface area ratio as the complete ensemble is the *Sauter* mean diameter, which is equivalent to the average particle size.

In addition, the definitions of the *Reynolds* number and the friction factor may vary across sources. These differences are further compounded by the diversity of experimental systems used to develop correlations, including spherical particles, rough solids, cylinders, extrudates, porous particles, and ring-shaped packings. Consequently, the reported coefficients, validity ranges, and predictive accuracy of pressure-drop correlations may differ significantly, even for beds with apparently similar geometrical characteristics. This issue is particularly important in RTES. In contrast to idealized particles, natural rocks are generally irregular, angular, rough, and often polydisperse, which makes defining a representative particle size more ambiguous and complicates the estimation of bed-scale hydraulic resistance. Accordingly, a structured comparison of the available friction-factor correlations is required before selecting or adapting a model for rock-bed applications.

On this basis, Table 1 provides an overview of the selected friction-factor correlations for predicting hydraulic resistance in packed beds, with a focus on their applicability to porous-medium and continuum-scale modeling. For each reference, the table presents the porosity range, packed-bed dimensions, particle or bed geometry, characteristic particle diameter, *Reynolds*-number range, bed-to-particle diameter ratio, and the corresponding friction-factor expression, converted where possible to a consistent definition based on the modified packed-bed *Reynolds* number, Re_p , and the packed-bed friction factor, f . The included correlations cover a wide range of packed-bed configurations, from classical spherical-particle beds, such as those considered by *Ergun*, *KTA*, and *Achenbach*, to more generalized formulations that account for particle roughness, porosity, wall effects, particle shape, and non-spherical storage elements. The table also includes correlations developed for air–rock beds and crushed-rock thermal storage systems, such as those of *Chandra–Willits* [15] and *Allen et al.* [16], which are especially relevant to RTES applications because they account for the effects of irregular particle shape, surface roughness, packing method, and particle orientation. More recent studies on pebble beds, structured beds, and high-temperature gas/solid storage systems are also included to illustrate the range of geometries and operating conditions encountered in practical packed-bed TES systems. Thus, the table serves not only as a source of friction-factor equations but also as evidence of the limited universality of any single correlation, since each model is associated with specific ranges of porosity, *Reynolds* number, particle morphology, and bed geometry. This makes the table an essential basis for the subsequent comparison plots and for discussing the suitability of different pressure-drop closures in continuum CFD models of RTES systems.

Table 1. Friction-factor correlations in packed beds.

Author (Year)	Packed Bed		Particle		Reynolds Number (Re_P) [-]	D_{PB}/D_P [-]	Correlation
	Porosity (ϵ) [-]	Dimensions D_{PB} (Diameter)/ L_{PB} (Length) [mm]	Shape	Diameter (D_P) [mm]			
Ergun (1949, 1952, and 1953) [23–25]	0.330–0.421 (0.260–0.764 [26])	25.4/762	Spherical and pulverized particles	0.2–1.0 (0.497–12.7 [26])	0.1–1000	25.4–127	$f = \frac{150}{Re_P} + 1.75$
Macdonald et al. (1979) [27]	0.123–0.919	44.5/355 (According to the available datasets)	Spheres, cylinders, irregular media, smooth and rough solids	0.012–109.73	10^{-5} – 10^3	0.41–3708.33 (According to the available datasets)	$f = \epsilon^{-0.6} \left(\frac{180}{Re_P} + 1.8 \right)$ (Smooth solids) $f = \epsilon^{-0.6} \left(\frac{180}{Re_P} + 4 \right)$ (Rough solids)
KTa (1981) [28]	0.36–0.42	-	Identical spherical pebbles	-	100 – 10^5	0–35	$f = \frac{160}{Re_P} + \frac{3}{Re_P^{0.1}}$
Chandra and Willits (1981) [15]	0.38–0.46	$310 \times 310/600$	Random natural rocks: river gravel and crushed granite	9.9–26.9	160–1850	11.5–31.3	$f = \frac{\epsilon^{0.4}}{1-\epsilon} \cdot \left(\frac{185}{(1-\epsilon)Re_P} + 1.7 \right)$
Achenbach (1995) [29]	0.387	983/840	Spherical particles/pebble bed	60	$\leq 10^5$	16.4	$f = A(1-\epsilon)^n Re^{-n}$ where $n = 1$ ($A = 160$) represents the low Re range and $n = 0.1$ ($A = 3$) the high one.
Lakota et al. (2002) [30]	0.375–0.58	172/1220	Nonporous and porous spheres, porous cylinders, porous extrudates, Raschig rings	1.8–6.0	0.51–193.2	28.7–95.6	$f = \frac{160}{Re_P} + B$ where $B = 1.75$ for spheres, $B = 3.0$ for cylinders, $B = 7.4$ for extrudates, and $B = 6.0$ for Raschig rings
Singh et al. (2006) [31]	0.306–0.63	600/750	T-joint masonry tile brick, standard masonry tile brick, standard masonry brick, concrete cube, concrete sphere $\psi = 0.55$ – 1.0	125–186	1500–7200	3.23–4.8	$f = 4.466 Re_P^{-0.2} \psi^{0.696} \epsilon^{0.055} (1-\epsilon)^{-1.2}$ $[exp\{11.85(\log\psi)^2\}]$
Harrison et al. (2013) [32]	0.33–0.88	Compiled datasets; no single bed dimension reported	Effective spherical particles/compiled packed-bed data	-	0.48 – 6.4×10^4	8.3–50	$f = \frac{119.8}{Re_P} \left(1 + \frac{\pi d_p}{6 D_{PB}(1-\epsilon)} \right)^2 + \frac{4.63}{Re_P^{1/6}} \left(1 - \frac{\pi^2 d_p}{24 D_{PB}} + \frac{0.5 d_p}{D_{PB}} \right)$
Singh et al. (2013) [33]	0.275–0.48	600/750	Concrete sphere, cube, and rectangular blocks ($\Psi = 0.65$ – 1)	60	694–1665	10	$f = 374.765 Re_P^{-0.6482} \psi^{2.5246} \epsilon^{2.2122} (1-\epsilon)^{-1.6482}$ $[exp\{9.7487(\ln\psi)^2\}]$
Allen et al. (2015) [16]	0.38–0.46	$260 \times 260/300$ for wind-tunnel tests; $1000 \times 1000/1500$ for high-temperature dolerite tests	Crushed rock: hornfels and dolerite	9–49	100–1000	9.3–26.8	Co-/counter-current packing $f = \frac{310}{Re_P} + \frac{6.85}{Re_P^{0.08}}$ Cross-current packing $f = \frac{300}{Re_P} + \frac{6.15}{Re_P^{0.14}}$
Singhal et al. (2018) [34]	0.405–0.539	-	Cylindrical particles/dense gas–solid packed beds	1	9–180	-	$f = \frac{284}{Re_P} + 2.67$

Table 1. Cont.

Author (Year)	Packed Bed		Particle		Reynolds Number (Re_p^*) [-]	D_{PB}/D_P [-]	Correlation	
	Porosity (ϵ) [-]	Dimensions D_{PB} (Diameter)/ L_{PB} (Length) [mm]	Shape	Diameter (D_P) [mm]				
Liu et al. (2018) [35]	0.361–0.377	80/300	Randomly packed spherical pebbles	8, 10	Transitional: 90–270 Turbulent: 270–2200	8–10	$90 \leq Re_p \leq 270$ $270 \leq Re_p \leq 2200$	$f = \frac{4.15Re_p^{0.85}-102.7}{Re_p}$ $f = \frac{135}{Re_p} + 0.923$
Esence et al. (2019) [36]	0.4	$800 \times 800/5000$	Structured cordierite ceramic plates forming corrugated vertical channels	8	50–1333	-	$f = 321.1 \times Re_p^{-1.6364} + 0.3468$	

$$* Re_p = \frac{\rho_f \times u_{Superficial} \times D_P}{\mu_f \times (1-\epsilon)}.$$

Before presenting the correlations in Table 1, it should be noted that different studies used different definitions of particle diameter, *Reynolds* number, porosity correction, and friction factor. Therefore, where possible, the pressure-drop correlations were rewritten using a common packed-bed friction-factor form and the modified particle *Reynolds* number adopted in this review. The particle diameters reported in the table correspond to the nominal, average, equivalent, or effective diameters provided in the original references. No universal conversion to a *Sauter* mean diameter was performed when the required particle-size distribution, external surface area, or sphericity information was not available. Consequently, the converted forms should be interpreted as comparison forms for continuum CFD implementation rather than exact replacements of the original experimental definitions.

A comparison of selected classical packed-bed friction-factor correlations, plotted on log–log axes over a wide Re_p range at $\varepsilon = 0.4$, is shown in Figure 1. The comparison plot is limited to correlations that can be expressed mainly as a direct function of the modified packed-bed *Reynolds* number, Re_p , with little or no dependence on additional geometric or particle-shape parameters. Therefore, Ergun [23–25], KTA [28]/Achenbach [29], Macdonald et al. [27], and Liu et al. [35] are selected because they provide general packed-bed friction-factor formulations and can be compared directly after converting them to the same definitions of Re_p and f . The study by Macdonald et al. [27] was included because it extends the Ergun-type formulation by distinguishing between smooth and rough particles. In contrast, the study by Liu et al. [35] was included because it provides a more recent experimental correlation for packed-sphere/pebble beds over a defined transitional–turbulent range. Other correlations were not included in this plot because they introduce additional dependencies that would make the comparison less direct: Chandra–Willits [15] and Allen et al. [16] are rock-bed-specific; Singh et al. [31,33] depend strongly on particle sphericity and large storage-element geometry; Harrison et al. [32] explicitly include wall effects through the packed bed; Esence et al. [36] include a structured-channel bed correlation and an Ergun-based granular-bed application; and Singhal et al. [34] is a heat-transfer/Nusselt-number study rather than a friction-factor correlation. These correlations are better compared in dedicated plots for rock beds, shape effects, wall effects, or structured beds.

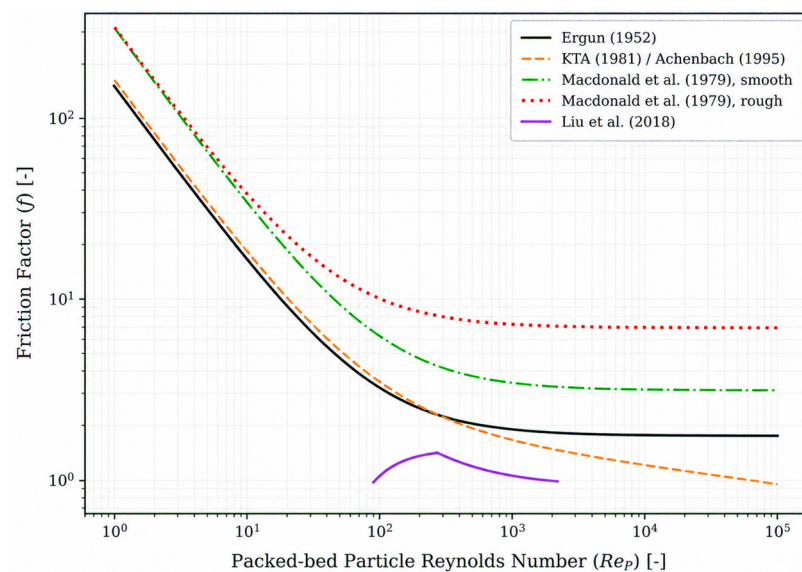


Figure 1. Comparison of selected packed-bed friction-factor correlations over a wide range of Re_p values at $\varepsilon = 0.4$. These correlations were selected because they can be expressed primarily as functions of Re_p , allowing direct comparison using consistent definitions of Re_p and f .

Figure 1 shows that most selected general packed-bed friction-factor correlations decrease with increasing Re_p , reflecting the reduced relative contribution of viscous resistance as inertial effects become more dominant. However, the Liu et al. [35] correlation exhibits a noticeably different piecewise and non-monotonic behavior in the transitional range, where the predicted packed-bed friction factor increases with Re_p before decreasing again in the turbulent branch. The authors indeed reported an increase in the packed-bed friction factor in the transitional regime. They attributed it to an unstable flow transition characterized by wake oscillations and vortex formation. This difference is mainly caused by the piecewise structure of the correlation and the transitional flow regime considered in their packed pebble-bed experiments. In the transitional range, $90 \leq Re_p \leq 270$, the correlation is expressed as $f = (4.15 \times Re_p^{0.85} - 102.7)/Re_p$ or equivalently $f = 4.15 \times Re_p^{-0.15} - 102.7 \times Re_p^{-1}$. In this form, the negative Re_p^{-1} contribution decreases rapidly as Re_p increases, which can produce an increasing friction-factor trend over the transitional interval. For $270 \leq Re_p \leq 2200$, the turbulent branch changes to $f = 135/Re_p + 0.923$, which again decreases with increasing Re_p and approaches an asymptotic inertial value. Therefore, the shape of the Liu et al. [35] correlation reflects the empirical transition between flow regimes in their randomly packed spherical pebble bed. Liu et al. [35] attributed this transitional behavior to the development of an unstable flow, characterized by wake oscillations and vortex formation. Consequently, although the Liu et al. [35] correlation is useful as a recent pebble-bed reference, it should be applied only within its reported validity range. It should not be directly generalized to irregular rock-bed RTES systems without system-specific validation.

At low Re_p values, most correlations exhibit a strong $1/Re_p$ -type dependence, although the predicted magnitudes differ because each model uses different empirical constants and was developed from different datasets. The Ergun correlation provides a classical baseline and gradually approaches a constant inertial limit at high Re_p values. In contrast, the KTA [28]/Achenbach [29] correlation remains close to Ergun at low-to-moderate Re_p values but predicts a continuously decreasing high- Re_p behavior due to the $Re_p^{-0.1}$ term rather than a fixed inertial plateau. The smooth and rough Macdonald et al. [27] correlations predict friction factors that are noticeably higher than those of Ergun, especially at intermediate and high Re_p values, because the porosity correction $\varepsilon^{-0.6}$ and the larger inertial constants amplify the hydraulic resistance; the difference between the smooth and rough cases clearly illustrates the strong influence of particle surface condition on pressure loss. The Liu et al. [35] correlation is valid only within its reported range. It predicts lower friction factors than most classical correlations, which may be related to its specific pebble-bed geometry, limited porosity range, and high Prandtl number. Overall, the plot demonstrates that even among relatively general packed-bed correlations, predicted hydraulic resistance can differ substantially, particularly outside the low- Re_p viscous regime.

To further examine the influence of bed structure and particle morphology on hydraulic resistance, Figure 2 compares the sensitivity of selected friction-factor correlations to porosity, shape, and surface roughness. In Figure 2a, the correlations are evaluated at a fixed sphericity of $\psi = 0.8$ while varying porosity, thereby isolating the effect of void fraction on f . In Figure 2b, the porosity is fixed at $\varepsilon = 0.4$. At the same time, the sphericity in the Singh et al. [31,33] correlations and the smooth/rough cases in Macdonald et al. [27] are varied to highlight the role of particle shape and surface condition in pressure-drop prediction.

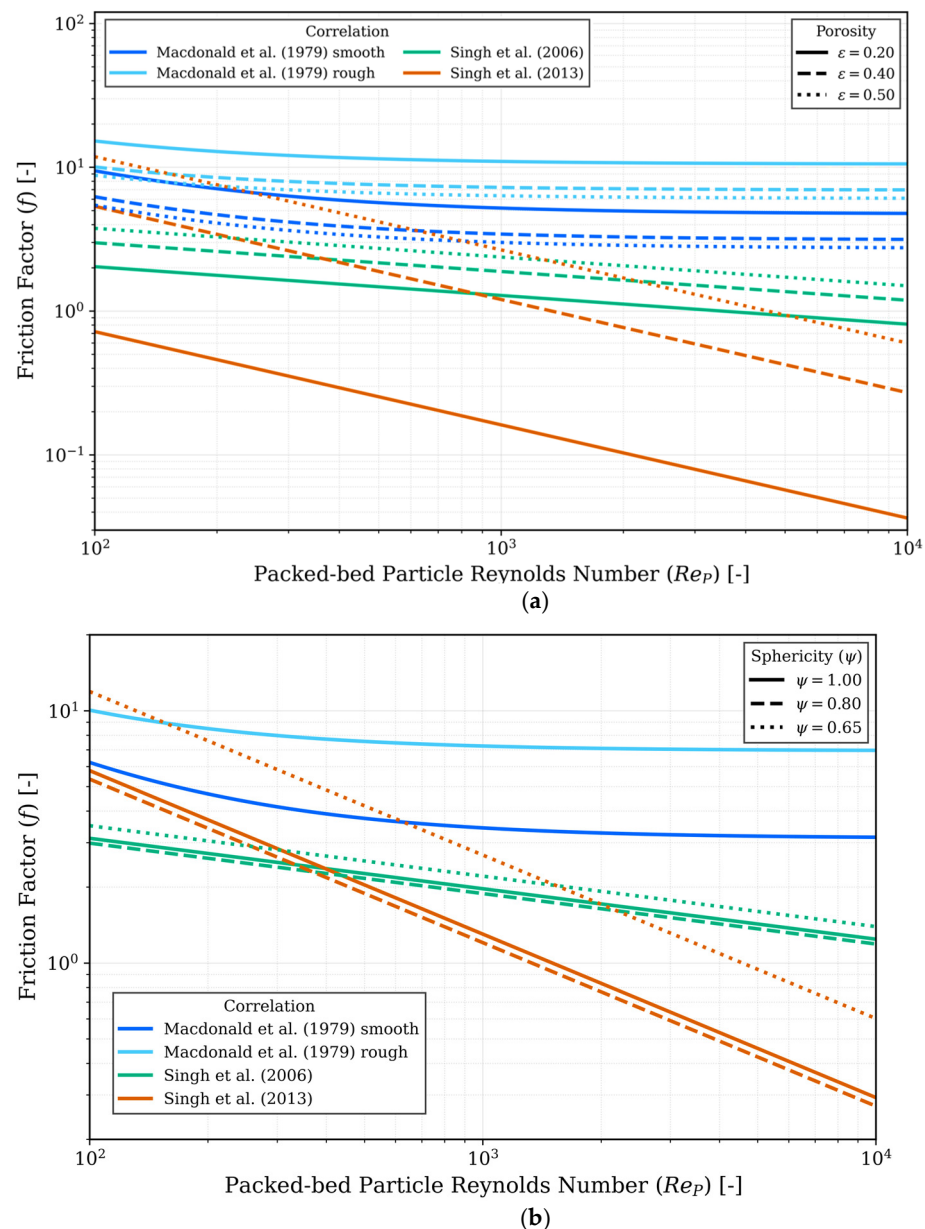


Figure 2. (a) Porosity sensitivity comparison of selected friction-factor correlations at $\psi = 0.8$, and (b) shape and roughness sensitivity comparison of selected friction-factor correlations at $\varepsilon = 0.4$ (The Macdonald et al. [27] correlations are independent of ψ).

Figure 2a shows that the predicted sensitivity of the packed-bed friction factor to porosity is strongly correlation-dependent, indicating that porosity effects are not represented consistently across the selected models. In this comparison, the sphericity (ψ) is fixed at ($\psi = 0.8$) for the Singh et al. [31] and Singh et al. [33] correlations, while the Macdonald et al. [27] correlations do not include a sphericity term. For the Macdonald et al. [27] correlations, decreasing porosity increases f because the correlation includes the multiplier $\varepsilon^{-0.6}$; therefore, denser beds are predicted to exhibit greater dimensionless hydraulic resistance. This trend is physically consistent with the expectation that a lower void fraction increases flow constriction and resistance. The rough-particle version of Macdonald et al. [27] remains consistently higher than the smooth-particle version because of the larger inertial coefficient, showing that surface condition can be as important as porosity. In contrast, the Singh et al. [31] and Singh et al. [33] correlations show an opposite trend in porosity for the converted f form, with higher porosity leading to larger predicted values. This behavior

results from the specific empirical porosity dependence embedded in these correlations after conversion to the common Re_p and f definitions, and it should therefore be interpreted carefully as a dimensionless friction-factor trend rather than a direct statement that higher porosity always causes a larger absolute pressure drop. It should also be noted that some plotted porosity values, particularly ($\varepsilon = 0.2$) and partially ($\varepsilon = 0.5$), fall outside the original validity ranges of the Singh et al. [31] and Singh et al. [33] correlations and are shown only for comparative visualization. Among the plotted models, Singh et al. [33] exhibits the strongest combined sensitivity to both Re_p and porosity, as indicated by its steep $Re_p^{-0.6482}$ dependence and its strong converted porosity terms. Singh et al. [31] shows a milder *Reynolds*-number dependence, proportional to $Re_p^{-0.2}$, and a more moderate porosity effect. By contrast, the Macdonald et al. [27] approach a weaker *Reynolds*-number dependence and porosity-dependent asymptotic friction-factor values at a higher Re_p value. Overall, Figure 2a demonstrates that the predicted role of porosity can vary substantially depending on the experimental database, particle geometry, and the friction-factor definition used to develop the correlation, reinforcing the need to select pressure-drop closures based on the porosity and particle characteristics of the target packed-bed TES system.

Figure 2b shows that particle shape and surface condition can strongly affect the predicted packed-bed friction factor, even when porosity is fixed at $\varepsilon = 0.4$. The Macdonald et al. [27] rough-particle formulation gives consistently higher f values than the smooth-particle formulation because it uses a larger inertial coefficient, confirming that surface roughness can significantly increase hydraulic resistance, especially in the intermediate and high- Re_p ranges where inertial effects dominate. For the Singh et al. [31,33] correlations, changing the sphericity affects the predicted friction factor differently. In Singh et al. [31], the non-spherical cases do not follow a simple monotonic trend because the correlation includes both a power-law term in ψ and an exponential correction involving $(\log \psi)^2$, reflecting the complex influence of large storage-element geometry on flow paths. Similarly, Singh et al. [33] shows a strong but non-monotonic dependence on sphericity: the original study reported the minimum friction factor for cubical elements ($\psi = 0.8$). In contrast, lower-sphericity rectangular elements and spherical elements produced higher resistance. This behavior reflects the combined influence of angularity, flatness, particle contact mode, and packing arrangement on the flow field. The contrast between the roughness effect of Macdonald et al. [27] and the sphericity effect of Singh [31,33] shows that a single parameter cannot represent particle morphology; surface roughness, angularity, flatness, and packing arrangement may influence pressure drop differently. Overall, Figure 2b shows that correlations developed for non-spherical or rough particles can deviate substantially from those for smoother particles, particularly in RTES systems where natural rocks are irregular, rough, and randomly oriented.

To specifically assess pressure-drop prediction for RTES systems, the rock-bed-specific correlations of Chandra–Willits [15] and Allen et al. [16] are compared with the classical Ergun [23–25] correlation, used as a benchmark, in Figure 3. These correlations were selected because those developed by Chandra–Willits [15] and Allen et al. [16] are based on airflow through beds of natural or crushed rocks and therefore more closely represent the effects of irregular particle shape, surface roughness, packing characteristics, and flow arrangement that are typical of RTES systems. The Ergun correlation, in contrast, represents a conventional reference derived primarily from more idealized packed beds. Thus, this comparison highlights the differences between rock-bed-specific formulations and the classical benchmark, and helps clarify the extent to which using a general packed-bed correlation may underpredict or misrepresent the hydraulic resistance of practical rock-bed storage systems.

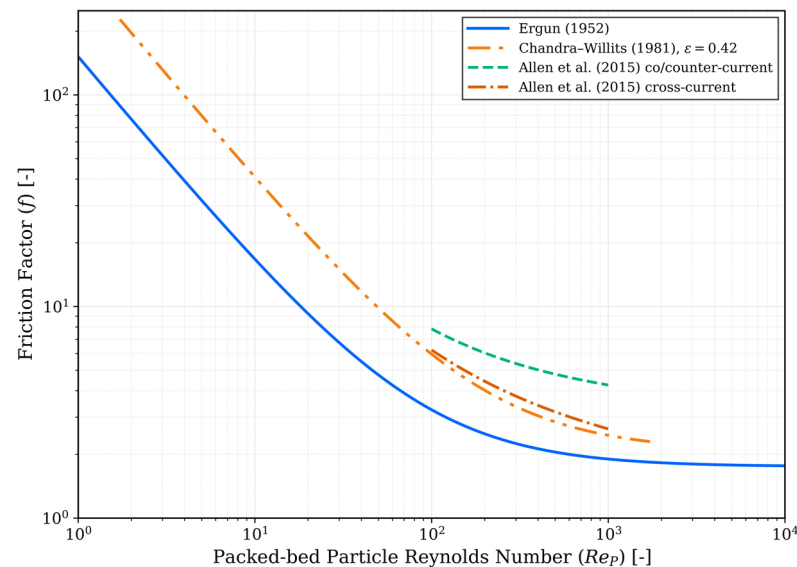


Figure 3. RTES friction-factor comparison: f versus Re_p for Chandra–Willits [15], Allen et al. [16], and the Ergun [23–25] benchmark at $\varepsilon = 0.42$.

As shown in Figure 3, the rock-bed-specific correlations predict friction factors that are significantly larger than those of the classical Ergun benchmark over most of the plotted Reynolds-number range. This difference is expected, as natural and crushed rocks introduce additional hydraulic resistance due to their irregular shape, angularity, rough surfaces, random orientation, and non-uniform packing. In contrast, the Ergun equation was developed for more idealized packed-bed conditions. Similar to the Ergun correlation, the Chandra–Willits correlation [15] decreases with increasing Re_p but predicts higher values because it was developed from air–RTES experiments. Within the overlapping Reynolds-number range, the Allen et al. [16] co-/counter-current correlation yields the highest friction-factor values. In contrast, the cross-current correlation predicts lower values that remain above the Ergun curve and close to, or higher than, the Chandra–Willits correlation. This behaviour highlights the strong influence of crushed-rock morphology and packing direction on pressure loss. The difference between the co-/counter-current and cross-current Allen et al. curves [16] further shows that the same rock material can exhibit different hydraulic resistance when the packing orientation changes relative to the airflow.

The Allen et al. [16] correlations predict the highest f values, especially at higher Re_p values, and their curve shapes differ from both the Ergun [23–25] and Chandra–Willits [15] correlations. This behavior is mainly caused by the empirical structure of the Allen et al. [16] correlations, which were developed from crushed rock beds of hornfels and dolerite under different packing orientations. For the co-/counter-current and cross-current arrangements, the correlations include weak Reynolds-number power-law terms, $Re_p^{-0.08}$ and $Re_p^{-0.14}$, respectively. These terms decrease much more slowly with Re_p than a classical $1/Re_p$ viscous term; therefore, the predicted friction factor remains relatively high and varies more gradually across the plotted range. Physically, this reflects stronger inertial and form-drag effects from angular crushed rocks, rough surfaces, non-uniform void spaces, and packing orientation relative to the airflow. The co-/counter-current packing produces higher friction factors than the cross-current packing, consistent with Allen et al. [16], who reported that the pouring/packing direction of crushed rock relative to the airflow can significantly alter pressure-drop behavior. Therefore, the distinct shape of the Allen et al. [16] curves is attributed to both their crushed-rock experimental basis and their correlation form, rather than to a numerical or plotting issue.

To better quantify the differences between the selected pressure-drop closures, Figure 4 presents the relative deviation of each major friction-factor correlation from the *Ergun* benchmark. This deviation factor is important because direct comparison of the f curves can make differences difficult to interpret, especially on logarithmic axes, whereas the relative deviation explicitly indicates whether each correlation predicts higher or lower hydraulic resistance than the classical reference, and by how much. In this figure, all correlations are plotted only within their reported or converted validity ranges for Re_P , and comparisons are performed under the selected benchmark conditions of $\varepsilon = 0.4$, $\psi = 0.8$, and $D_{PB}/D_P = 20$, where applicable. Therefore, Figure 4 helps identify correlations that may significantly overpredict or underpredict pressure drops under the selected benchmark conditions. This is particularly important for continuum CFD modeling because errors in hydraulic resistance directly affect the predicted pressure drop, airflow distribution, blower power requirements, and the overall thermo-hydraulic performance of RTES systems.

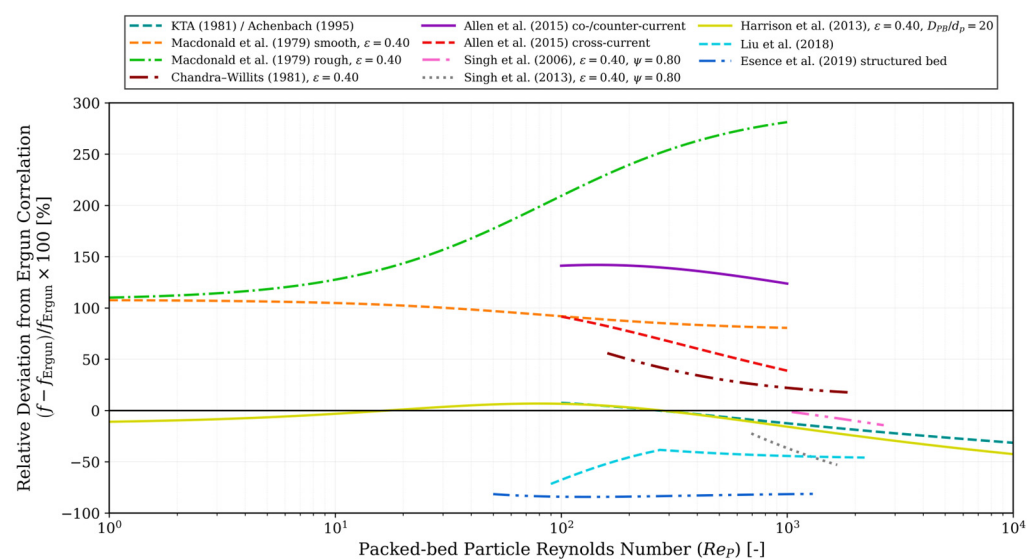


Figure 4. Relative deviation of major packed-bed friction-factor correlations from the *Ergun* benchmark, at $\varepsilon = 0.40$, $\psi = 0.80$, and $D_{PB}/D_P = 20$.

Figure 4 shows that deviations from the *Ergun* benchmark [23–25] are highly correlation-dependent, confirming that the choice of pressure-drop closure can strongly affect the predicted hydraulic resistance. The *Macdonald* rough-particle formulation yields the largest positive deviation among the compared correlations, increasing from approximately 110% to 280% relative to the *Ergun* benchmark over its plotted validity range. This corresponds to friction-factor values approximately 2.1 to 3.8 times those predicted by *Ergun*, highlighting the strong influence of particle roughness and inertial resistance. The *Macdonald* [27] smooth case also remains above *Ergun*, with a positive deviation of approximately 80–110%, indicating that even moderate modifications to the *Ergun* constants can noticeably increase the predicted pressure drop. The rock-bed-specific correlations of *Chandra–Willits* [15], and of *Allen et al.* [16], generally remain above *Ergun*’s correlations, supporting the idea that irregular natural or crushed rocks introduce additional resistance compared with idealized packed beds; however, their deviations decrease or vary with Re_P , reflecting their different empirical structures and experimental ranges. Among them, the *Allen et al.* [16] co-/counter-current correlation gives a larger positive deviation than the cross-current correlation, demonstrating the sensitivity of crushed-rock pressure loss to packing orientation and flow direction.

In contrast, several correlations predict lower resistance than *Ergun* over part or most of their valid ranges. The *KTA/Achenbach* correlation is slightly above *Ergun* at lower Re_P ,

but becomes negative at higher Re_p . The Singh et al. [31] and Singh et al. [33] correlations at $\varepsilon = 0.4$ and $\psi = 0.8$ lie below the Ergun curve within their plotted validity ranges, indicating lower predicted friction factors under these conditions. Harrison et al. [32], which includes wall-effect correction through D_{PB}/d_p , remains close to Ergun at low-to-moderate Re_p but becomes increasingly negative at higher Re_p . Liu et al. [35] also predicts lower friction factors than Ergun over its transitional–turbulent validity range. Finally, the Esence et al. [36] structured-bed correlation shows the largest negative deviation, reflecting the reduced pressure loss in structured vertical channels compared with randomly packed beds. Overall, Figure 4 demonstrates that deviations from Ergun can range from strong underprediction to several hundred percent overprediction, emphasizing that Ergun should be treated as a reference rather than a universal closure, especially for continuum CFD modelling of rock-bed TES systems.

From a practical modelling perspective, the choice of pressure-drop correlation should be guided by the similarity between the target RTES configuration and the experimental conditions under which each correlation was developed. The Ergun correlation remains a useful classical benchmark and a preliminary CFD screening tool, especially when limited information is available. KTA- and Achenbach-type [28,29] correlations are more appropriate for spherical particles or pebble-bed configurations, while Macdonald-type [27] correlations are useful when the effect of surface roughness needs to be considered. For air–RTES systems composed of natural rocks, gravel, or crushed granite, the Chandra–Willits [15] correlation is more representative within its validity range. For crushed rock beds where particle morphology and packing orientation strongly affect hydraulic resistance, the Allen et al. [16] correlations are more suitable. Correlations developed for large non-spherical elements, wall-effect-sensitive beds, packed pebbles, or structured-channel beds should be used only when the target system has particle geometry, porosity, bed-to-particle diameter ratio, and Reynolds-number range similar to those of the reference system. Therefore, no single pressure-drop closure should be considered universally valid, and the final selection should be based on particle morphology, roughness, porosity, flow regime, bed geometry, and, whenever possible, validation against system-specific pressure-drop data.

Although Figure 4 provides a direct comparison of the relative deviations of the selected friction-factor correlations from the Ergun benchmark over a broad Reynolds-number range, each curve is meaningful only within the reported or converted validity range of the corresponding correlation. A full-range comparison over the plotted domain, therefore, does not necessarily provide a quantitative basis for closure selection, especially when the correlations were developed for different particle geometries, porosity ranges, Reynolds-number intervals, and bed configurations. In real RTES applications, the operating Re_p interval is limited by the selected particle size, bed porosity, airflow rate, fan capacity, and allowable pressure drop. Therefore, Reynolds-number regions outside the validity range of a given correlation, or outside the practical operating window of the target system, may be of limited relevance for closure selection in continuum CFD modeling. To provide a more quantitative and operationally oriented comparison, the relative-deviation curves were further summarized using weighted statistical indicators within the valid Re_p range for each correlation, rather than within a single common interval. This approach avoids extrapolating correlations outside their recommended applicability ranges and enables each model to be evaluated over the Reynolds-number interval for which it was developed or converted. Accordingly, the Re_p limits used for the statistical analysis were taken from the validity ranges summarized in Table 1 and are reported in Table 2 for each correlation. For each correlation, the analysis was performed using $N = 10$ logarithmically spaced Re_p points within each correlation's valid Re_p range, consistent with the logarithmic scale used in Figure 4. Equal weights were assigned to all points ($\omega_i = 1$), so the weighted indicators

represent the average deviation behaviour over the logarithmic *Reynolds*-number interval of each correlation.

Table 2. Weighted relative-deviation statistics of selected friction-factor correlations from the *Ergun* benchmark within the valid *Re_p* range of each correlation.

Correlation	<i>Re_p</i> Range	$\bar{\delta}_w$ [%]	WMAD [%]	WRMSD [%]	$ \delta _{MAX}$ [%]	δ Range [%]
KTA [28]	100–10,000	−12.07	14.39	17.63	31.43	−31.43 to 7.47
Macdonald et al., smooth [27]	1–1000	96.76	96.76	97.28	107.60	80.58 to 107.60
Macdonald et al., rough [27]	1–1000	178.74	178.74	189.55	281.23	110.11 to 281.23
Chandra–Willits [15]	160–1850	32.41	32.41	34.67	55.91	17.77 to 55.91
Allen et al., co-/counter-current [16]	100–1000	135.95	135.95	136.09	141.92	123.78 to 141.92
Allen et al., cross-current [16]	100–1000	65.82	65.82	68.02	91.62	38.85 to 91.62
Singh et al. [31]	1047–2674	−7.70	7.70	8.74	14.30	−14.30 to −1.39
Singh et al. [33]	694–1665	−38.58	38.58	39.80	52.98	−52.98 to −22.40
Harrison et al. [32]	1–10,000	−11.09	13.56	18.67	42.49	−42.49 to 6.47
Liu et al. [35]	90–2200	−47.92	47.92	48.83	71.55	−71.55 to −39.43
Esence et al. [36]	50–1333	−82.78	82.78	82.79	84.18	−84.18 to −81.25

The statistical indicators included the pointwise relative deviation δ_i , the weighted signed deviation $\bar{\delta}_w$, the weighted mean absolute deviation (WMAD), the weighted root-mean-square deviation (WRMSD), and the maximum absolute deviation (δ_{MAX}). These indicators were used to quantify the average tendency of each correlation to overpredict or underpredict the *Ergun* benchmark, the average magnitude of deviation, and the intensity of larger deviations within the practical RTES operating range. These indicators are as follows:

$$\delta_i = \left(\frac{f_i - f_{Ergun,i}}{f_{Ergun,i}} \right) \times 100 \quad (6)$$

$$\bar{\delta}_w = \frac{\sum_{i=1}^N \omega_i \times \delta_i}{\sum_{i=1}^N \omega_i} \quad (7)$$

$$WMAD = \frac{\sum_{i=1}^N \omega_i \times |\delta_i|}{\sum_{i=1}^N \omega_i} \quad (8)$$

$$WRMSD = \left(\frac{\sum_{i=1}^N \omega_i \times \delta_i^2}{\sum_{i=1}^N \omega_i} \right)^{1/2} \quad (9)$$

In the above equations, *i* denotes each *Reynolds*-number point used in the statistical analysis, while *N* is the total number of points considered within the valid *Re_p* range of each correlation. In the present analysis, *N* = 10 was used for each correlation, corresponding to 10 logarithmically spaced *Reynolds*-number points between the lower and upper limits of the valid *Re_p* range reported for that correlation. The term *f_i* represents the friction factor predicted by a given correlation at the *i*-th *Reynolds*-number point, and *f_{Ergun,i}* is the corresponding friction factor obtained from the *Ergun* benchmark. The parameter δ_i therefore represents the pointwise relative deviation of each correlation from *Ergun*. The weighting factor ω_i defines the relative importance assigned to each *Reynolds*-number point. Since no detailed operating-frequency distribution was available for a specific target RTES, uniform weighting was adopted, with $\omega_i = 1$ for all *Reynolds*-number points. Thus, all 10 logarithmically spaced points within the valid *Re_p* range of each correlation were treated equally. The weighted signed deviation, $\bar{\delta}_w$, indicates the average tendency of a correlation to predict higher or lower friction factors than *Ergun*. The WMAD represents the average magnitude of deviation regardless of sign, while the WRMSD gives greater influence to larger deviations. The maximum absolute deviation, $|\delta|_{MAX}$, indicates the largest pointwise

difference observed within the valid Re_p range of each correlation. Since *Ergun* was used as a benchmark rather than experimental data, these indicators should be interpreted as relative-deviation statistics rather than absolute prediction errors. The calculated indicators for the valid Re_p range of each selected correlation are listed in Table 2.

Table 2 shows that the predicted deviation from the *Ergun* benchmark is strongly dependent on the selected friction-factor correlation, even when each model is evaluated only within its own valid Re_p range. The *KTA/Achenbach* [28,29] and *Harrison et al.* [32] correlations remain relatively close to *Ergun*, with small weighted signed deviations; however, *Harrison et al.* [32] exhibits a larger maximum absolute deviation than *KTA/Achenbach* because its wall-effect correction varies with Re_p over a wider validity range. In contrast, the *Macdonald et al.* rough-particle formulation [27] shows the largest positive deviation, confirming the strong influence of surface roughness and inertial resistance on pressure-drop prediction. The *Macdonald* smooth case [27] also predicts higher resistance than *Ergun*, but with a smaller deviation than the rough-particle case. The rock-bed-specific correlations of *Chandra–Willits* [15] and *Allen et al.* [16] remain above the *Ergun* benchmark, which is consistent with the additional hydraulic resistance expected in natural or crushed rock beds due to irregular particle shape, angularity, rough surfaces, and non-uniform packing. Among these, the *Allen et al.* [16] co-/counter-current correlation shows the second-largest positive deviation after the *Macdonald* rough-particle case, whereas the *Allen* cross-current correlation gives a lower but still positive deviation, highlighting the influence of packing orientation and flow direction. Conversely, *Singh et al.* [31,33], *Liu et al.* [35], and *Esence et al.* [36] predict lower friction factors than *Ergun* within their valid Re_p ranges under the selected comparison conditions. The negative deviations of the *Singh et al.* correlations reflect their dependence on particle sphericity and porosity, while the *Liu et al.* [35] trend is associated with its packed-pebble transitional–turbulent experimental basis. The *Esence et al.* [36] structured-channel correlation shows the strongest negative deviation, reflecting the reduced pressure-loss behavior of structured vertical channels compared with randomly packed beds. Overall, the weighted statistics confirm that the choice of pressure-drop closure can substantially affect the predicted hydraulic resistance in continuum CFD modeling of RTES systems, and that the operating *Reynolds*-number interval and the similarity between the target rock bed and the original experimental conditions of each correlation should guide that selection.

Finally, the analyzed friction-factor correlations show that hydraulic resistance in packed beds is highly sensitive to particle morphology, porosity, bed geometry, wall effects, and packing arrangement. Classical correlations, such as the *Ergun* correlation [23–25], are useful as baselines for continuum porous-medium modeling. Still, they cannot be considered universally valid for RTES systems, especially when the storage medium consists of natural or crushed rocks with irregular shapes, rough surfaces, wide size distributions, and non-uniform packing. The comparison of correlations shows that rock-bed-specific models, particularly those derived from air–rock-bed experiments, tend to predict higher friction factors than the *Ergun* benchmark [23–25]. In contrast, correlations developed for structured or geometry-specific beds may yield lower resistance, depending on the flow arrangement. The sensitivity analyses also indicate that porosity, sphericity, roughness, and the bed-to-particle diameter ratio can significantly influence pressure drop and, consequently, blower power, flow distribution, thermal-front propagation, and overall thermo-hydraulic performance. Thus, the pressure-drop closure used in continuum CFD simulations of RTES systems should be selected based on the similarity between the correlation’s experimental conditions and those of the target system, rather than on convenience or common practice. System-specific calibration or validation against experimental pressure-drop data is recom-

mended whenever possible to reduce uncertainty and improve the reliability of large-scale RTES design and optimization.

3. Fluid–Solid Heat-Transfer Correlations in RTES Systems

Heat-transfer correlations are important closure relations in continuum models of packed-bed and RTES systems because they determine the rate of energy exchange between the heat-transfer fluid and the solid storage medium. In porous-medium modeling, the complex pore-scale interactions between the flowing fluid and individual particles are not explicitly resolved; therefore, the convective heat-transfer process must be represented using empirical or semi-empirical relations, commonly expressed in terms of the Nusselt number, heat-transfer coefficient, or volumetric heat-transfer coefficient. These correlations are typically dependent on parameters such as *Reynolds* number, *Prandtl* number, porosity, particle diameter, particle shape, bed-to-particle diameter ratio, and flow arrangement. However, as with pressure-drop correlations, heat-transfer correlations are often developed under specific experimental conditions, including particle materials, bed geometries, temperature ranges, and flow regimes. Thus, their validity ranges and underlying assumptions must be carefully evaluated before they are applied in continuum CFD simulations of RTES systems, especially when natural or crushed rocks with irregular geometries and wide size distributions are used as the storage medium.

Table 3 presents a summary of selected heat-transfer correlations reported for packed-bed systems and provides the main information required to evaluate their applicability to the continuum modelling of RTES systems. For each reference, the table lists the porosity range, packed-bed dimensions, particle type and diameter, *Reynolds*-number range, bed-to-particle diameter ratio, temperature range, and the proposed heat-transfer correlation. These characteristics are included because heat-transfer correlations are highly dependent on the experimental setup in which they were developed, including particle morphology, bed geometry, flow regime, and thermal operating conditions. In addition, the table distinguishes among correlations expressed in terms of the surface heat-transfer coefficient, the volumetric heat-transfer coefficient, or the Nusselt number, since these forms are not directly interchangeable without proper conversion. Therefore, presenting the experimental conditions and correlation type for each reference helps clarify the validity range of each model and supports a more reliable selection of heat-transfer closures for continuum CFD simulations of rock-bed thermal energy storage systems. For the heat-transfer correlations summarized in Table 3, the equations were expressed, where possible, in terms of the particle Nusselt number to enable direct comparison among models. When correlations were originally reported using a heat-transfer coefficient, they were converted using the corresponding particle diameter, fluid thermal conductivity, and interfacial area definition stated or implied in the original source. Because some studies did not report complete particle-size distributions or surface-area information, the particle diameter used in each converted expression follows the definition available in the original reference. Therefore, when applying these correlations to a new RTES system, the particle diameter definition and validity range of the original correlation should be retained whenever possible.

Table 3. Summary of the selected heat-transfer correlations for packed-bed systems.

Reference	Bed Porosity (ϵ) [-]	Bed Dimensions [mm] (D_{PB}/L_{PB})	Particle Type and Diameter (D_p) [mm]	Particle Reynolds Number (Re_{p*1}) [-]	D_{PB}/D_p [-]	Temperature Range [°C]	Correlation for Particle Nusselt Number (Nu_p) [-]
Furnas (1930) [37]	0.395–0.506	150/1050	Iron Balls: 18.5, 31.7, and 48.6	99.2–2348	8.1–4.7–3.1	400–750	$Nu_p = 0.253 \times u^{0.75} \times T_K \times 10^{1.68\epsilon - 3.56\epsilon^2} \times \frac{D_p}{k_f}$
Leva (1947) [38]	0.37–0.447	50.8/914.4 and 12.7/279.4	- Glass balls: 4.37, 5.79, 9.8, 3.2, 3.3, 3.6; - Clay balls: 8.83; - Porcelain balls: 12.89	240–6400	3.33–20	22.5–171.66	$Nu_p = 0.813 \times \frac{D_p}{D_{PB}} \times e^{-6(\frac{D_p}{D_{PB}})} \times ((1 - \epsilon) \times Re_p)^{0.9}$
Löf and Hawley (1948) [39]	0.426–0.454	267/914	Granitic gravel; equivalent spherical: 7.98, 12.52, 21.23, 33.32	87–916	33.4, 21.3, 12.6, 8.0	37.77–121.11	$Nu_p = 108.6 \times (1 - \epsilon)^{-0.3} \times \frac{\mu_f^{0.7} \times D_p^{0.6}}{k_f} Re_p^{0.7}$
Baumeister and Bennett (1958) [40]	0.354	101.6/1524	High-carbon chromium steel spheres: 3.95, 6.34, and 9.51	310–16,100	25.7, 16.0, 10.7	31.7–146.7	$Nu_p = 1.09 \times (1 - \epsilon)^{0.68} \times Re_p^{0.68} \times Pr^{1/3}$
De Acetis and Thodos (1960) [41]	0.482	93.78/82.55	Porous spheres (Johns-Manville Type VIII catalyst carrier): 15.9 ± 0.127	25–4124	5.9	11.55–32.22	$Nu_p = (1 - \epsilon) \times Re_p \times Pr^{1/3} \times \left(\frac{1.1}{((1 - \epsilon) \times Re_p)^{0.41} - 1.5} \right)$
Lancashire et al. (1960) [42]	0.4	1219.2/3169.92	Alumina/aluminum-oxide balls: 10.5	468–1285	116.1	171.29–1115.74	$Nu_p = 0.4 \times (1 - \epsilon)^{0.563} \times Pr^{\frac{1}{3}} \times Re_p^{0.563}$
Gupta and Thodos (1962) [43]	0.444, 0.576, and 0.778	127/177.8	Water-saturated celite spheres: 15.875	108–13,514	8	17.39–28.33	$Nu_p = 2.06 \times \left(\frac{(1 - \epsilon)^{0.425} \times Re_p^{0.425} \times Pr^{\frac{1}{3}}}{\epsilon} \right)$
Gupta and Thodos (1964) [44]	0.444, 0.576, and 0.778	127/177.8	Water-saturated celite spheres: 15.875	108–13,514	8	17.39–28.33	-
Gunn (1978) [45]	0.35–1	NA *2	General particle systems	$\leq 10^5 / (1 - \epsilon)$	-	NA	$Nu_p = (7 - 10 \times \epsilon + 5 \times \epsilon^2) \times$ $\left(1 + 0.7 \times ((1 - \epsilon) \times Re_p)^{0.2} \times Pr^{\frac{1}{3}} \right) +$ $(1.33 - 2.4 \times \epsilon + 1.2 \times \epsilon^2) \times ((1 - \epsilon) \times Re_p)^{0.7} \times Pr^{\frac{1}{3}}$
Wakao et al. (1979) [46]	Not explicit	Not explicit	NA	25–14,167 ($\epsilon = 0.4$)	Not explicit	NA	$Nu_p = 2 + 1.1 \times ((1 - \epsilon) \times Re_p)^{0.6} \times Pr^{1/3}$
Chandra and Willits (1981) [15]	0.38–0.46	310 × 310/600	River gravel and crushed granite; equivalent sphere, 9.9–26.9	160–1850	11.5–31.3	15–90	$Nu_p = \frac{1.45 \times (1 - \epsilon)^{-0.3}}{6} \times Re_p^{0.7}$
Singh et al. (2006) [31]	0.306–0.63	600/750	T-joint masonry tile brick, standard masonry tile brick, standard masonry brick, concrete cube, concrete sphere, $D_p = 125$ –186 mm, $\psi = 0.55$ –1.0	1500–7200	3.23–4.8	NA	$Nu_p = 0.0728 \times Re_p^{0.75} \times \epsilon^{-1.62} \times \psi^{4.35} \times e^{(29.03 \times (\log \psi)^2)} \times (1 - \epsilon)^{-0.25}$
Allen et al. (2015) [16]	0.35–0.45	260/300 for wind-tunnel tests; 1000/1500 for high-temperature dolerite tests	Glass spheres, steel spheres, aluminum cubes, rounded marble rock, crushed hornfels, and crushed dolerite; 9.7–49	120–1100	9.3–26.8	<80; up to 530	$Nu_p = 1.15 \times [(1 - \epsilon) \times Re_p]^{0.6} \times Pr^{1/3}$

Table 3. Cont.

Reference	Bed Porosity (ϵ) [-]	Bed Dimensions [mm] (D_{PB}/L_{PB})	Particle Type and Diameter (D_P) [mm]	Particle Reynolds Number (Re_P^{*1}) [-]	D_{PB}/D_P [-]	Temperature Range [$^{\circ}\text{C}$]	Correlation for Particle Nusselt Number (Nu_P) [-]
Cerantola and Lane (2022) [47]	0.334–0.401	100/150	Particle-resolved CFD of uniform and Rosin–Rammler distributed spherical particles and polyhedral rock-like particles; 12.8–20	21.7–2400	5–7.8	10–27	$Nu_P = \frac{1-\epsilon}{\epsilon} \times \left[1.274 + 0.430 \times (\tau \times Re_P)^{0.58} \times Pr^{1/3} \right]$ where τ is the tortuosity (1.25–1.38).
Noël et al. (2023) [48]	0.36 and 0.41	100/100	Real gravel and basalt rock packings with arbitrary particle shapes, 8 mm and 16 mm	8.5–412	6.3 and 12.5	<327	$Nu_P = \frac{-0.46 + 1.77 \times \epsilon + 0.69 \times \epsilon^2}{\epsilon^3 - 1.6 \times (1-\epsilon) \times \epsilon^4 - 3 \times (1-\epsilon) \times \epsilon^7 \times \exp \left[-((1-\epsilon) \times Re_P)^{0.4} \times (1-\epsilon) \right]} + \frac{[1.37 - 2.4 \times \epsilon + 1.2 \times \epsilon^2] \times ((1-\epsilon) \times Re_P)^{0.7} \times Pr^{0.33}}{1 - 1.6 \times (1-\epsilon) \times \epsilon - 3 \times (1-\epsilon) \times \epsilon^4 \times \exp \left[-((1-\epsilon) \times Re_P)^{0.4} \times (1-\epsilon) \right]}$
Wu and Hibiki (2025) [49]	0.35–0.60	(10–983)/(4.06–1524)	Randomly packed spherical particles (copper, steel, glass, lead, brass, graphite, bronze); 0.46–60	Laminar: 3–305 Turbulent: 1500–500,000	1.27–193 ($L/D_P = 2$ –240)	NA ($0.7 \leq Pr \leq 17$)	Laminar flow: $Nu_P = \frac{1-\epsilon}{\epsilon} \times \left[0.14 \times (\epsilon \times Re_P)^{0.9} \times Pr^{0.33} \times \epsilon^{-0.62} \times \left(\frac{L_{PB}}{D_P} \right)^{0.2} \right]$ Turbulent flow: $Nu_P = \frac{1-\epsilon}{\epsilon} \times \left[0.35 \times (\epsilon \times Re_P)^{0.7} \times Pr^{0.33} \times \left(\frac{D_{PB}}{D_P} \right)^{0.19} \right]$

*1 $Re_P = \frac{\rho_f \times u_{\text{Superficial}} \times D_P}{\mu_f \times (1-\epsilon)}$; *2 NA: not available.

The selected heat-transfer correlations and the information summarized in Table 3 are important because they provide the closure relations required to represent fluid–solid energy exchange in continuum and porous-medium models of packed-bed and RTES systems. Since the pore-scale interaction between air and storage particles is not explicitly resolved in these models, the accuracy of the predicted thermal-front propagation, charging/discharging rate, outlet temperature evolution, and overall storage efficiency depends strongly on the choice of heat-transfer correlation. The correlations in the table were selected to cover the main historical and technical developments in packed-bed heat-transfer modeling, ranging from early dimensional correlations and volumetric heat-transfer coefficients to Nu_P -based, dispersion-corrected, and rock-bed-specific formulations. They also represent different packed-bed configurations, including spherical particles, gravel, crushed rocks, alumina pebbles, wet porous spheres, and generalized fixed- or fluidized-particle beds. The listed columns were selected because each correlation applies only under specific experimental and modeling conditions. Therefore, parameters such as porosity, bed dimensions, particle type and diameter, particle *Reynolds* number range, *Prandtl* number range, bed-to-particle diameter ratio, temperature range, and correlation form are required to evaluate whether a given model is appropriate for RTES applications. Presenting the correlations in a uniform Nu_P -based format also enables direct comparisons among models. It highlights the limitations of applying correlations developed for ideal spherical beds or wet-particle systems to natural or crushed-rock storage media. Thus, Table 3 is not only a compilation of heat-transfer equations, but also a basis for selecting appropriate closure models for continuum CFD simulations and for identifying cases where experimental validation or system-specific calibration is needed.

Figure 5 compares selected particle–fluid heat-transfer correlations for packed-bed systems in terms of the particle Nusselt number, Nu_P , as a function of the packed-bed particle *Reynolds* number, Re_P . All correlations in Table 3 are presented in the common particle-based form $Nu_P = (h_{fs} \times D_P) / k_f$, allowing direct comparison even though the original definitions, experimental conditions, particle geometries, and validity ranges differ. Because both axes are logarithmic, the slope of each curve indicates the *Reynolds*-number dependence of the corresponding correlation, particularly for power-law-dominated regions. In general, Nu_P increases with increasing Re_P for all correlations, confirming that particle–fluid heat transfer in packed beds is enhanced by stronger forced convection. However, the predicted Nu_P values differ considerably among the correlations, especially at moderate and high *Reynolds* numbers. This spread mainly arises from differences in particle shape, porosity, wall effects, bed dimensions, flow regime, temperature range, and the definition of the characteristic particle diameter.

Figure 5a presents a broad comparison of the directly plottable selected heat-transfer correlations listed in Table 3, using the unified particle *Reynolds*-number definition (Re_P) and the specified operating/geometrical parameters. It can be observed that the predicted heat-transfer intensity differs by more than one order of magnitude over some *Reynolds*-number ranges, highlighting the strong sensitivity of Re_P predictions to the selected closure and to the original experimental or numerical database used to develop each correlation. The classical correlations are shown in Figure 5b. They generally exhibit similar increasing trends with Re_P , but differ in both slope and magnitude. For example, the *Baumeister* and *Bennett* [40] correlation predicts relatively high Nu_P values at high Re_P , whereas the *Lancashire* et al. [42] correlation predicts much lower values within its narrower validity range. The *Gunn* [45] and *Wakao* et al. [46] correlations provide intermediate predictions and are often used as general packed-bed benchmarks, although their applicability should still be interpreted in relation to particle type, porosity, and the *Reynolds*-number definition used in the original studies. More recent correlations are compared in Figure 5c, covering large

storage elements, crushed-rock beds, particle-resolved CFD datasets, real rock packings, and broad spherical-particle databases. These recent models display a wide range of behavior because they are based on different physical assumptions, characteristic particle diameters, and geometric descriptors. Allen et al. [16] and Cerantola–Lane [47] used particle-size definitions based on the volume-equivalent diameter and the Sauter mean diameter, respectively, while Singh et al. [31] incorporated sphericity to account for large non-spherical storage elements. Noël et al. [48] considered real gravel and basalt packings obtained from pore-scale simulations. Since the controlling parameters for laminar and turbulent flow differ, the Wu–Hibiki [49] correlations for these two regimes exhibit distinct trends. Overall, Figure 5 demonstrates that using a single universal heat-transfer correlation for all packed-bed TES configurations may lead to substantial uncertainty, and correlation selection should therefore consider particle morphology, bed structure, porosity, *Reynolds*-number range, and the characteristic length scale used in the original formulation.

It should be noted that the laminar and turbulent heat-transfer correlations proposed by Wu–Hibiki [49] are regime-dependent and should be applied within their respective validity ranges. Developing a new continuous correlation for the transition-flow regime would require dedicated validation analysis against relevant experimental or high-fidelity numerical data, particularly for transient RTES systems. Such a validation should evaluate not only the predicted particle Nusselt number, but also its effect on the interphase heat-transfer coefficient, outlet temperature, thermocline development, charging/discharging rate, and stored/released energy. This task is beyond the scope of the present review, which focuses on evaluating and comparing existing closure correlations for continuum porous-medium CFD modelling of RTES systems. Therefore, when an RTES system operates in the transition region between the laminar and turbulent regimes, a single fitted power-law correlation is not recommended unless it is independently validated. Instead, the transition region should be treated as an uncertainty interval, and sensitivity analysis using the laminar and turbulent correlations as lower/upper bounding cases is recommended.

In Tables 1 and 3, the reported particle diameters correspond to the average, nominal, equivalent, or effective diameters provided in the original references. No universal post-conversion to a *Sauter* mean diameter was applied because many studies do not provide the complete sieve distribution, particle counts, external surface area, or sphericity information required for a reliable conversion. Therefore, the *Sauter* mean diameter is introduced here as an important reference definition for packed-bed modelling, rather than as a recalculated value for all reviewed studies. When applying a selected correlation to a new RTES system, the particle diameter definition should be kept consistent with that used in the original correlation whenever possible. If only nominal or volume-equivalent diameters are available, the resulting uncertainty should be assessed through sensitivity analysis, especially for irregular or crushed rocks.

The correlations of greatest interest for RTES systems are shown in Figure 5d. This comparison suggests that RTES-specific correlations do not collapse onto a universal curve, even when they are evaluated using a unified *Reynolds*-number definition and common input parameters. The differences among Chandra–Willits [15], Allen et al. [16], Cerantola–Lane [47], and Noël et al. [48] indicate that the prediction of particle–fluid heat transfer in rock beds remains sensitive to particle morphology, porosity, tortuosity, packing structure, and the selected characteristic length scale. Thus, while classical correlations, such as those of Wakao et al. [46], remain useful benchmarks, more recent rock-specific and pore-scale-derived correlations may be better suited to realistic, irregularly packed rock beds when their validity ranges and geometric assumptions are consistent with the target RTES configuration. Overall, the large dispersion in correlations suggests that selecting an appropriate Nu_p correlation is a critical modeling decision in packed-bed TES simulations,

particularly for irregular rock beds, where particle shape, porosity, tortuosity, packing structure, and the definition of characteristic diameter significantly influence the predicted interphase heat-transfer coefficient.

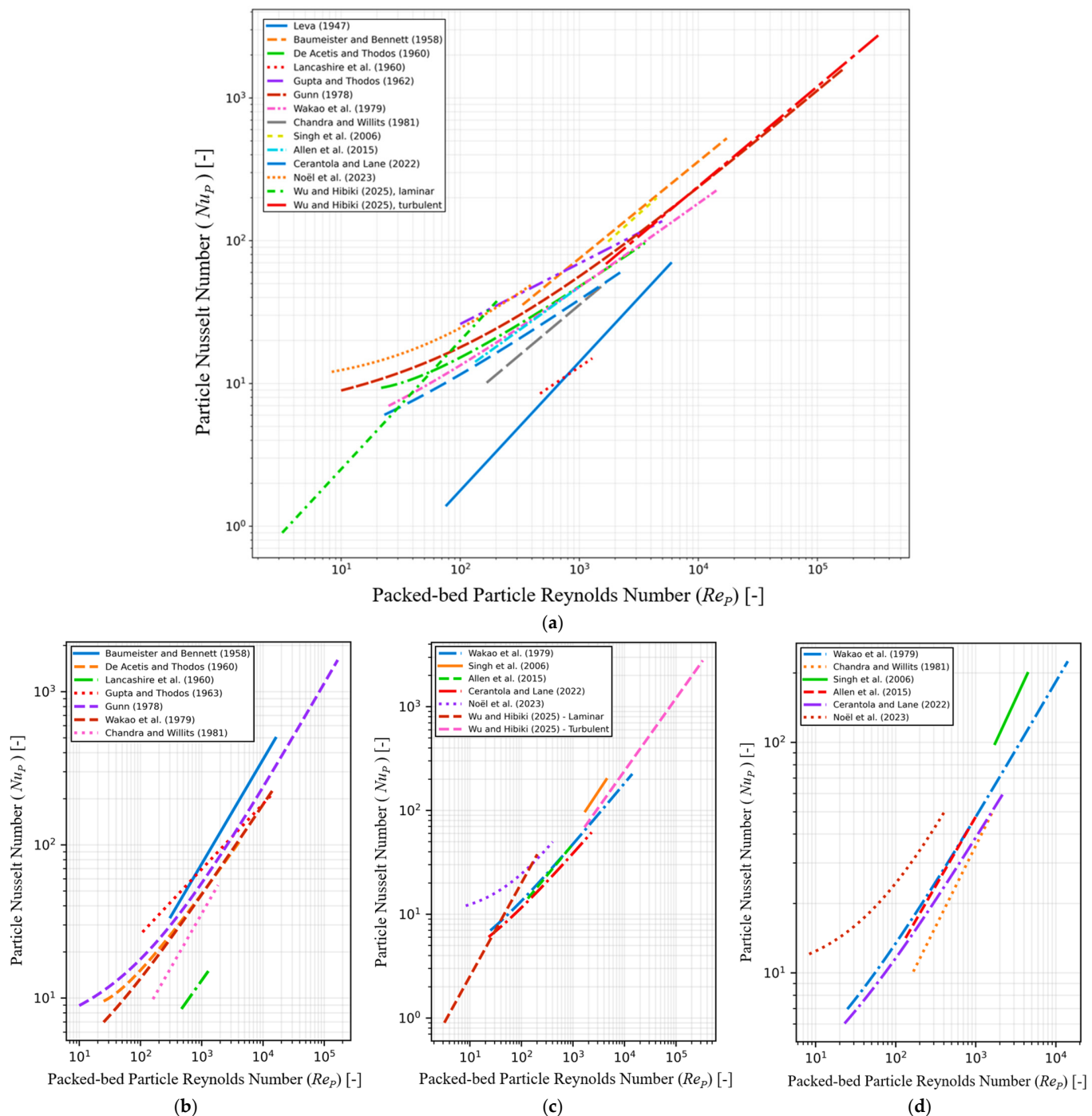


Figure 5. Comparison of (a) selected packed-bed heat-transfer correlations (listed in Table 3), (b) classical packed-bed heat-transfer correlations, (c) recent packed-bed heat-transfer correlations, and (d) RTES-relevant heat-transfer correlations in terms of particle Nusselt number (Nu_p) versus the packed-bed particle Reynolds number (Re_p), at $\varepsilon = 0.4$, $Pr = 0.7$, $D_{PB}/D_P = 10$, $L_{PB}/D_P = 50$, $\psi = 1.0$, and $\tau = 1.3$.

Figure 5b compares classical packed-bed heat-transfer correlations after expressing them in the same particle-based Nusselt-number form. For completeness, the air-rock-bed correlation of Chandra–Willits [15] is also included in this comparison as an RTES-

relevant reference. A key observation is that the classical correlations do not only differ in magnitude; they also imply different sensitivities of interphase heat transfer to Re_p . The Wakao et al. [46] correlation includes a finite low- Re_p baseline and then increases moderately as forced convection strengthens, which explains why it is often used as a general reference. Gunn [45] predicts slightly higher values because the study accounts explicitly for porosity effects in both low- and high- Re_p contributions. In contrast, Baumeister and Bennett [40] show a stronger Reynolds-number dependence, leading to a rapid increase in Nu_p at higher Re_p . The Lancashire et al. [42] correlation gives the lowest predictions within its narrow validity range, indicating that correlations derived from specific particle materials and bed configurations may substantially underpredict heat transfer when used as general closures. The Chandra–Willits [15] correlation, although directly relevant to air–rock beds, remains below several general correlations after conversion from their original volumetric form, suggesting that rock-bed-specific correlations are not necessarily higher than those of classical sphere-based models. Therefore, Figure 5b shows that the main uncertainty is not only the absolute value of Nu_p , but also the assumed scaling of heat transfer with the Re_p . This is important for RTES simulations because a stronger Re_p dependence will predict greater sensitivity to airflow rate, directly affecting the estimated charge/discharge rate, thermocline development, and LTE/LTNE coupling strength.

In Figure 5c, the focus shifts to recent packed-bed correlations developed using more advanced experimental databases, CFD simulations, pore-scale modeling, and broader data-driven parameter assessment. This group shows greater diversity in physical formulations than the classical models. For instance, Singh et al. [31] accounted for the effect of large non-spherical storage elements through the inclusion of sphericity, while Allen et al. [16] proposed a simplified correlation for air–rock beds using the volume-equivalent particle diameter. At the same time, Cerantola–Lane [47] incorporated tortuosity and the Sauter mean diameter through particle-resolved CFD. Noël et al. [48] used real gravel and basalt geometries obtained from tomographic data, thereby making their model more representative of realistic rock morphology. Wu–Hibiki [49] proposed separate correlations for the laminar and turbulent regimes, reflecting that different mechanisms and controlling parameters dominate in each. The separation between the laminar and turbulent Wu–Hibiki [49] curves also emphasizes that a single power-law relation may not adequately represent the full Re_p range in packed beds. Overall, this category demonstrates the recent shift from simple empirical fitting toward geometry-aware, regime-specific, and structure-sensitive heat-transfer modeling.

Figure 5d shows the correlations most relevant to this review in the context of RTES. Compared with the classical correlations, these models are more closely related to practical RTES systems because they account for crushed rock, real rock morphology, large storage elements, or rock-like numerical packings. The comparison shows that RTES-oriented correlations do not converge to a single trend, even after being expressed using a common Re_p and Nu_p definition. This is important because real rock beds are not ideal spherical-particle systems: they contain angular particles, rough surfaces, broad size distributions, non-uniform contact areas, irregular void networks, and tortuous flow paths. Allen et al. [16], Chandra–Willits [15], and Noël et al. [48] are more representative of experimental air–rock-bed configurations, although they differ in particle type, characteristic diameter, and modelling approach. In contrast, Cerantola–Lane [47] provides more detailed pore-scale or CFD-based descriptions of complex particle geometries, including tortuosity effects through a pore-scale Reynolds-number formulation. Therefore, the spread among these curves reflects real physical differences in the packed structures rather than only mathematical uncertainty. For RTES simulations, this means the selected heat-transfer correlation can strongly affect the predicted charging/discharging rate, thermocline thick-

ness, and the solid–fluid temperature difference. Accordingly, RTES-oriented correlations should be selected based on similarity between the target bed and the original experimental or numerical conditions, rather than solely on their apparent agreement with classical packed-bed benchmarks.

Together, the three categories clearly show a progression in the modelling of packed-bed heat transfer. The classical correlations provide broad empirical reference points, but simplified particle geometries often limit their applicability. The recent correlations introduce more detailed descriptors, such as tortuosity, hydraulic diameter, *Sauter* mean diameter, sphericity, and regime-dependent parameters. The RTES-focused correlations are most relevant to realistic thermal storage applications, but they are also highly sensitive to particle morphology and the definition of length scales. This comparison confirms that interphase heat-transfer modelling in rock-packed beds remains highly correlation-dependent, and that the selected Nu_p model should be consistent with the particle type, flow regime, porosity, and characteristic diameter, and original validity range used in the RTES model. Therefore, correlation selection should not be treated as a purely mathematical fitting choice, but as a physical modelling decision that can directly influence the predicted interphase heat-transfer coefficient, thermal stratification, charging/discharging dynamics, and overall energy-storage performance.

Figure 6 further evaluates the selected heat-transfer correlations by plotting their relative deviation from the *Wakao et al.* [46] benchmark. This representation is useful because direct comparison of the Nu_p curves alone does not always clearly show the magnitude and direction of disagreement between models, especially on logarithmic axes. In this plot, the zero line represents the *Wakao et al.* [46] correlation, while positive and negative deviations indicate overprediction and underprediction, respectively, relative to this benchmark. The plotted segments also reflect the validity range of each correlation after conversion to the common Re_p -based formulation. The results show that several correlations deviate substantially from those reported by *Wakao et al.* [46], with some models predicting Nu_p values approximately 50–125% higher within specific Re_p ranges, while others remain below the benchmark. For example, *Baumeister–Bennett* [40], *Gupta–Thodos* [43], *Singh et al.* [31], *Noël et al.* [48], and *Wu–Hibiki* [49] generally show positive deviations over part of their validity ranges. *Gunn* [45] and *Acetis–Thodos* [41] also show *Reynolds*-number-dependent deviations, approaching the *Wakao et al.* [46] benchmark over limited intervals but remaining noticeably different elsewhere. In contrast, *Chandra–Willits* [15], *Allen et al.* [16], *Cerantola–Lane* [47], and *Lancashire et al.* [42] tend to predict lower values than those of *Wakao et al.* [46] within the plotted ranges. Figure 6 also shows that the deviation is *Reynolds*-number-dependent; some correlations approach the *Wakao* [46] benchmark over a limited Re_p intervals, whereas others diverge progressively as the Re_p increases. This behaviour confirms that the uncertainty is not uniform across the flow regime, but depends strongly on the *Reynolds*-number range and on the original assumptions used to develop each closure. Therefore, Figure 6 provides a clearer measure of the uncertainty associated with selecting a given heat-transfer closure relation and demonstrates the potential impact of correlation choice on continuum CFD predictions of interphase heat transfer in RTES systems, including the predicted interphase heat-transfer coefficient, solid–fluid temperature difference, thermocline evolution, and charge/discharge performance.

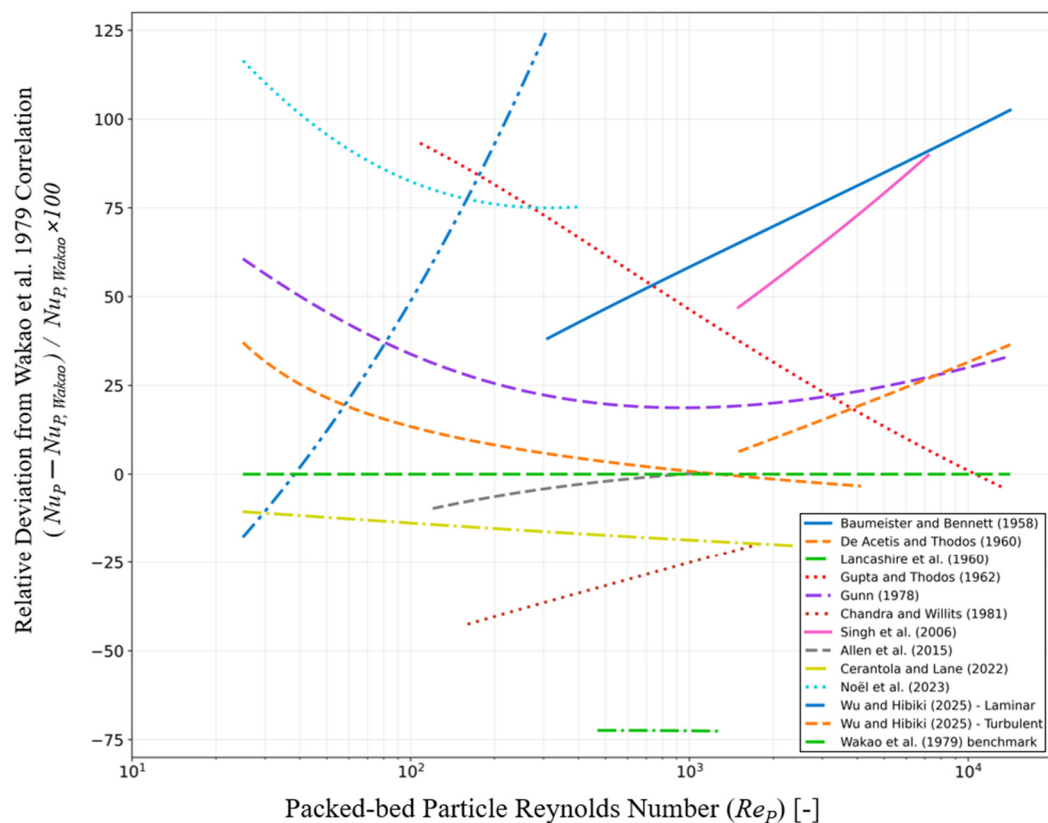


Figure 6. Relative deviation of selected packed-bed heat-transfer correlations from the *Wakao et al. (1979)* [46] benchmark, at $\varepsilon = 0.4$, $Pr = 0.7$, $D_{PB}/D_P = 10$, $L_{PB}/D_P = 50$, $\psi = 1.0$, and $\tau = 1.3$ (positive values indicate higher predicted particle Nusselt numbers than *Wakao et al. (1979)* [46], while negative values indicate lower predictions).

The relative-deviation results in Figure 6 show that the selected correlations differ substantially from the *Wakao et al. [46]* benchmark, even under the same representative conditions of $Pr = 0.7$ and $\varepsilon = 0.4$, with additional geometric or model-specific parameters kept fixed where required by the corresponding correlations. The zero line represents the *Wakao et al. [46]* correlation; therefore, positive deviations indicate a higher predicted Nu_P , while negative deviations indicate lower predictions. Among the classical correlations, *Baumeister–Bennett* [40] increasingly overpredicts Nu_P as the Re_P increases, indicating a stronger *Reynolds*-number dependence than the *Wakao et al. [46]* correlation. *Gunn* [45] also predicts higher values over most of the plotted range, although its deviation is more moderate. *Gupta–Thodos* [43] shows large positive deviations at lower Re_P values, but the deviation decreases with increasing Re_P , whereas *Acetis–Thodos* [41] approaches the *Wakao* [46] benchmark at intermediate-to-high *Reynolds* numbers. In contrast, *Lancashire et al. [42]* and *Chandra–Willits* [15] predict lower Nu_P values than the *Wakao* [46] benchmark over their plotted ranges. This indicates that even correlations with similar increasing Nu_P trends can produce opposite deviations relative to the same benchmark, depending on their *Reynolds*-number exponent, porosity treatment, and original experimental basis.

The recently added correlations also show noticeable deviations from the *Wakao et al. [46]* benchmark. *Singh et al. [31]* and *Noël et al. [48]* generally predict higher Nu_P values, while *Allen et al. [16]* and *Cerantola and Lane [47]* remain below the benchmark over most of their validity ranges. The positive deviations of *Singh et al. [31]* are mainly associated with its inclusion of particle sphericity for large non-spherical storage elements, whereas the deviations of *Noël et al. [48]* reflect the use of real gravel and basalt geometries obtained from pore-scale data. The *Wu–Hibiki* [49] laminar and turbulent correlations

show different deviation trends, reflecting their separate regime-dependent formulations. In particular, the laminar *Wu–Hibiki* [49] correlation changes from lower to substantially higher predictions as Re_p increases within its validity range, while the turbulent correlation remains above the *Wakao et al.* [46] benchmark in the plotted range. Overall, these differences demonstrate that the choice of heat-transfer closure can introduce significant uncertainty into the predicted interphase heat-transfer coefficient, particularly when correlations derived from spherical beds, generalized packed beds, large storage elements, CFD-based rock-like packings, or real rock geometries are applied outside their original experimental or numerical context. Therefore, the deviation trends in Figure 6 reinforce the need to select the heat-transfer closure with validity-range checking and sensitivity analysis, rather than adopting a single benchmark correlation without considering bed morphology and flow regime.

4. Methodological Framework for Porous-Medium Modelling of RTES Systems

The continuum porous-medium approach, which does not explicitly resolve the individual rock particles, can be used to model the fluid flow and heat transfer in RTES systems. In this approach, the packed bed is modeled as a homogeneous porous region, characterized by porosity, an equivalent particle diameter, hydraulic resistance, effective thermal properties, and an interphase heat-transfer coefficient. This framework is particularly useful for engineering-scale CFD simulations, as pore-scale modelling of realistic rock beds is computationally expensive and often impractical for full storage-system analysis. Two thermal models can be distinguished: the local thermal equilibrium (LTE) model, in which the fluid and solid phases are assumed to have a common local temperature, and the local thermal non-equilibrium (LTNE) model, in which separate energy equations are solved for the air and rock phases. The LTE model is a simplified approximation that is valid when heat transfer between the fluid and the solid is sufficiently strong. The LTNE model is more appropriate for transient charging and discharging processes, where a finite temperature difference between the flowing air and the solid storage medium may exist.

Continuum models, also known as volume-averaged models (VAMs) or Porous-Media Models (PMMs), for modeling heat transfer and fluid flow in porous media, apply a macroscopic approach to represent the complex interactions within the porous structure. Instead of resolving the detailed pore-level geometry and flow paths, these models treat the porous medium as a homogenized or continuous domain. This approach simplifies the mathematical description of fluid flow and heat transfer by averaging the effects of microscale features over a representative elementary volume (REV), which is sufficiently large to encompass a statistically representative portion of the pores and the solid matrix, yet small enough relative to the porous medium's overall dimensions. The key principles of the continuum model are as follows:

- *Homogenization:* The process involves averaging the physical properties (such as velocity, pressure, and temperature) and the governing equations (such as the Navier–Stokes equations for fluid flow, heat conduction, and convection equations for thermal analysis) across the REV. This yields macroscopic properties (e.g., permeability and effective thermal conductivity) and equations describing the system's average behavior.
- *Effective Properties:* Continuum models use effective properties to account for the influence of the pore structure on fluid flow and heat transfer. These include effective permeability, which describes the ease of fluid flow through the porous medium, and effective thermal conductivity, which represents the medium's ability to conduct heat. These properties are crucial for accurately predicting the system's macroscopic behavior.

- *Darcy's Law and Extensions:* In fluid flow, models often rely on Darcy's law or its extensions (e.g., the Brinkman equation) to describe flow through porous media. These laws relate the macroscopic flow rate to the medium's pressure gradient, viscosity, and permeability.
- *Energy Equation:* The energy conservation equation in continuum models accounts for effective thermal conductivity and can capture both conduction and convection within the porous medium, providing a comprehensive description of heat transfer processes.

Continuum models are widely used in engineering and geosciences for applications ranging from groundwater flow analysis and oil and gas recovery to heat exchangers and chemical reactors, as well as thermal management in electronics and energy systems. The main advantages of these models include:

- *Simplified Analysis:* By averaging over the REV, continuum models reduce the complexity of modeling porous media, enabling analysis of large domains without the prohibitive computational costs of resolving every pore.
- *Versatility:* These models can be applied to a wide range of porous materials and conditions, provided that the effective properties can be accurately estimated or measured.
- *Integration with Classical Engineering Tools:* The macroscopic equations derived from continuum models can be readily implemented in standard CFD and heat transfer simulation software, allowing for the analysis of complex systems involving porous media.

Regarding this model's limitations, averaging processes may overlook local variations and microscale phenomena that could be significant in specific applications. Moreover, the accuracy of continuum models depends heavily on accurate estimates of effective properties, which can be challenging in heterogeneous or anisotropic porous media. Continuum models for porous media are a class of methods that provide macroscopic descriptions of heat transport and fluid flow in porous media. These models, which average the effects of the microscopic structure over a representative volume, come in a few main varieties, each with particular uses and assumptions. Each continuum model is tailored to specific types of porous media challenges, balancing computational efficiency and the level of detail necessary to capture the essential physics of the processes involved. The model choice depends on the porous medium's specific characteristics, the flow and transport phenomena of interest, and the scales at which these processes occur.

Figure 7 compares the two main modelling scales used for porous media. In the pore-scale model, the real pore geometry, solid particles, local velocity field, and local temperature gradients are resolved directly; therefore, the governing equations are solved within the actual void space between particles, providing detailed microscale information but incurring very high computational cost. In contrast, the continuum-averaged model replaces the complex pore structure with a homogeneous porous block and uses volume-averaged variables, such as average velocity, pressure, and temperature, along with effective properties, including porosity, permeability, and effective thermal conductivity. In this approach, the microscopic interactions between the fluid and particles are not explicitly resolved but are represented through closure relations, such as *Darcy–Forchheimer* pressure-drop terms and *LTE/LTNE* heat-transfer equations. Therefore, the figure shows that both approaches describe the same physical system, but at different levels of detail: pore-scale modeling is more accurate for local transport mechanisms, while continuum-averaged modeling is more practical for engineering-scale simulations of RTES systems.

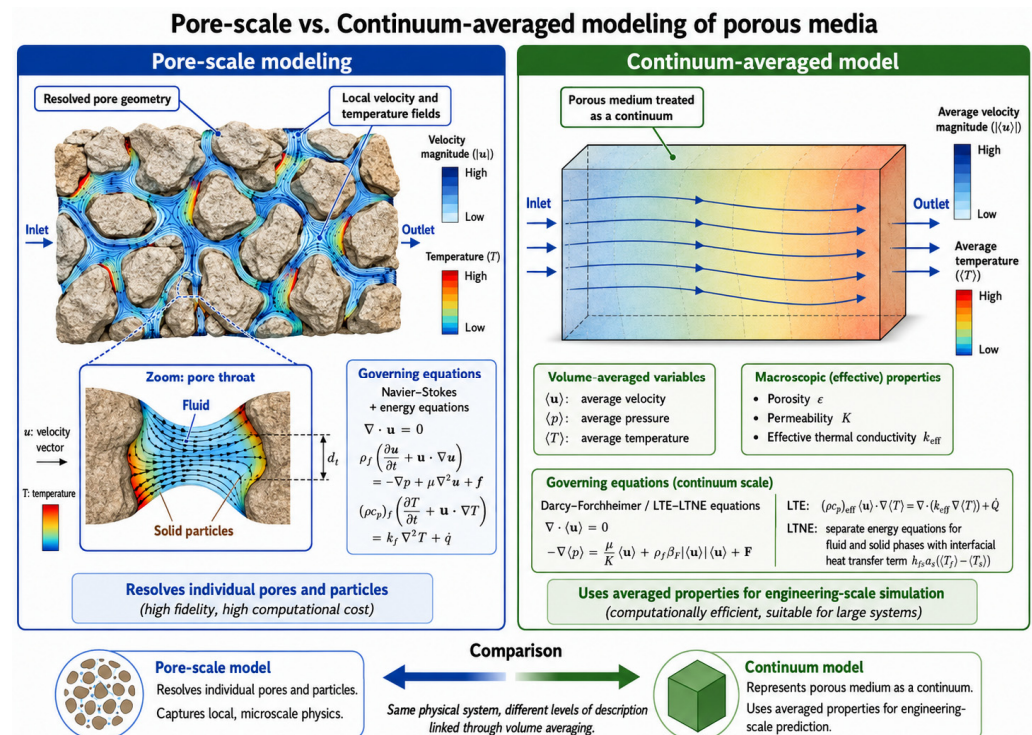


Figure 7. Pore-scale and continuum-averaged modelling approaches for porous media.

4.1. Flow Field Modeling

A simplified macroscopic technique that views the porous media as a continuous structure is called the continuum-averaged method. All of the intricacies and minute characteristics of the microscopic pore structure are converted into bulk terms in this model (such as permeability, which reflects the medium's average properties). Empirical correlations such as Darcy's Law, the Blake–Kozeny–Carman equation (BKC), or Ergun's equation [23–25] fit within this category. The significant advantage of the continuum medium method lies in its compact equation form, which describes highly complex phenomena in porous media using a small number of simplified terms. As a result, continuum medium models can be used readily without incurring additional computational costs. However, these methods have a significant limitation: they do not account for pore-scale flow physics (microscopic properties).

4.1.1. Darcy's Law

Darcy's Law is one of the descriptions of fluid flow in porous media. Henry Darcy formulated this law using experimental results [50,51]. Maurice Muskat has rewritten Darcy's Law to obtain the flow rate in a porous medium under constant-head conditions (Equation (10)).

$$\dot{Q} = - \frac{\kappa \times A \times \Delta p}{\mu_f \times L_{PB}} \quad (10)$$

Equation (10) applies to single-phase fluid flow and represents the characteristic equation for single-phase permeability. The overall flow rate ($\dot{Q}$) is equal to the multiplication of intrinsic permeability (κ) in the cross-sectional area of the flow region (A) and the total pressure drop ($\Delta p = p_i - p_o$), divided by the viscosity (μ_f) and the length of the section causing the pressure drop (L_{PB}). The negative sign indicates that the fluid is flowing from an area of higher pressure to an area of lower pressure. The earliest version of Darcy's Law was a linear Newtonian model that connected the local pressure gradient (Δp) along the flow path (L_{PB}) to the superficial/Darcy velocity (rate of volumetric flow per cross-sectional

area unit, $\dot{q} = \dot{Q}/A$). This relationship considers the fluid viscosity (μ_f) and porous-medium permeability (κ). In actuality, *Darcy's Law* is the most used model for explaining flow in porous material:

$$\frac{|\Delta p|}{L_{PB}} = \frac{\mu_f \times \dot{q}}{\kappa} \quad (11)$$

Although *Darcy's Law* is an empirical connection, it may be obtained by applying the Navier–Stokes equations in a homogeneous condition (connecting microscopic laws to the macroscopic scale) to the *capillary tubes* model. *Darcy's Law* has been extracted from basic principles using a number of different approaches. The majority of these approaches, however, are largely based on the fluid-phase momentum balance equations, according to theoretical considerations. When applied to laminar flow under low-*Reynolds*-number circumstances, *Darcy's Law* solely takes into account the viscous term and leaves out any inertial factors. When the *Reynolds* number is less than one, the porous medium's flow regime is usually laminar. The flow enters the nonlinear region as velocity rises, and the impact of inertia becomes noticeable. *Darcy's law* may become inaccurate when inertial effects, unsteady effects, non-Newtonian behavior, multiphase flow, or strong pore-scale heterogeneity become significant. Heat transport and boundary-layer effects are not accounted for in the *Darcy* flow model. The validity of *Darcy's Law* is restricted to laminar, solely viscous, and Newtonian flows since the Darcy model essentially ignores any findings other than Newtonian viscous effects. In order to account for increasingly complicated phenomena like multiphase flows and non-Newtonian behaviors, *Darcy's Law* has been refined. Homogenization or volume-averaging methods have been used to infer a number of extensions, including nonlinear variables like inertia.

4.1.2. Blake–Kozeny–Carman (BKC) Model

This model for porous media is one of the most famous in fluid dynamics for describing flow in such environments. The BKC model assumes that a bundle of capillary tubes with a uniform diameter distribution can represent the porous medium. This model encompasses many equations developed for various conditions and assumptions, designed with standard, precise characteristics. This family of equations corrects for pressure drop in a porous medium using the superficial/*Darcy* velocity, fluid viscosity, medium porosity, and granule diameter (D_p). Additionally, it may be used to simulate the macroscopic characteristics of the porous media, such as permeability. Certain variations of this family depict the medium as a collection of direct tubes with average hydraulic pressures and complex cross-sectional areas. Alternative representations depict the porous medium as a collection of complex, winding tubes that fit the Navier–Stokes equation. The curvature effect on average channel velocity provides a more accurate representation of *Newtonian* fluids in natural porous media:

$$\frac{|\Delta p|}{L_{PB}} = \frac{72 \times C' \times \mu_f \times \dot{q} \times (1 - \varepsilon)^2}{D_p^2 \times \varepsilon^3} \quad (12)$$

where ε is porosity, and C' is the *Carman* coefficient.

The BKC model is mainly valid for creeping or low-*Reynolds*-number laminar flow in porous media, where viscous losses dominate, and kinetic energy dissipation caused by repeated contraction, expansion, and redirection of flow channels can be neglected (*Blake* [52]; *Kozeny* [53]; *Carman* [54,55]). Historically, the model was developed from the analogy between flow through a packed bed and *Hagen–Poiseuille* flow through a bundle of tortuous capillary channels, relating permeability or pressure drop to porosity, particle size, and specific surface area (*Kozeny* [53]; *Carman* [54,55]). The historical basis is generally *Blake* [52] for packed-bed resistance, *Kozeny* [53] for the capillary-bundle permeability

derivation, and Carman [54,55] for the granular-bed formulation and later generalization. Similar streamline-flow formulations for sand were also reported by Fair et al. [56]. For higher *Reynolds* numbers, where inertial effects become important, the Burke–Plummer [57] relation and later the Ergun equation [23–25] extended packed-bed pressure-drop modelling by adding an inertial loss contribution to the viscous Blake–Kozeny-type term (Burke and Plummer [57]; Ergun [23–25]).

The required geometric inputs are the packed bed length, L_{PB} , cross-sectional area, A_C , hydraulic diameter, D_H , porosity, ε , and equivalent particle diameter, D_P . The solid phase is defined by the density, ρ_s , specific heat capacity, $C_{p,s}$, and thermal conductivity, k_s , while the fluid phase is defined by ρ_f , μ_f , $C_{p,f}$, and k_f . The *Prandtl* number of the HTF is defined by $Pr = (C_{p,f} \times \mu_f) / k_f$.

The Darcy–Forchheimer momentum formulation may be used to characterize the fluid flow through the rock bed:

$$\frac{|\Delta p|}{L_{PB}} = \frac{\mu_f}{\kappa} u_{\text{Superficial}} + \frac{1}{2} \rho_f \times C_2 \times u_{\text{Superficial}}^2 \quad (13)$$

where C_2 is the coefficient of inertial resistance, and κ is the permeability. For porous-media modeling, viscous and inertial resistances should be provided as inputs and computed using the Ergun [23–25] equation. The link between the superficial/Darcy velocity and the pressure decrease along a porous bed in this model is quasi-empirical. This model is often used to represent the physical characteristics of porous materials and to visualize flow in them. Fluid and bed characteristics are the equation's inputs. A version of the formula uses the *Reynolds* number to adjust the friction factor. The Ergun [23–25] model includes both viscous and inertial effects, while the Darcy and Blake–Kozeny–Carman (BKC) models only contain viscous terms:

$$\frac{|\Delta p|}{L_{PB}} = \frac{150 \times \mu_f \times (1 - \varepsilon)^2}{D_P^2 \times \varepsilon^3} \times u_{\text{Superficial}} + \frac{1.75 \times \rho_f \times (1 - \varepsilon)}{D_P \times \varepsilon^3} \times u_{\text{Superficial}}^2 \quad (14)$$

which gives

$$\kappa = \frac{\varepsilon^3 \times D_P^2}{150 \times (1 - \varepsilon)^2} \quad (15)$$

$$C_2 = \frac{3.5 \times (1 - \varepsilon)}{\varepsilon^3 \times D_P} \quad (16)$$

For RTES applications, a rock-bed-specific pressure-drop closure is more appropriate because natural and crushed rocks are irregular, rough, and non-spherical. The Chandra–Willits-type [15] pressure-drop correlation is expressed as follows:

$$\frac{|\Delta p|}{L_{PB}} = \varepsilon^{-2.6} \times \left[\frac{185 \times \mu_f}{D_P^2} \times u_{\text{Superficial}} + \frac{1.7 \times \rho_f}{D_P} \times u_{\text{Superficial}}^2 \right] \quad (17)$$

which can be converted to the Darcy–Forchheimer coefficients as

$$\kappa = \frac{D_P^2}{185 \times \varepsilon^{-2.6}} \quad (18)$$

$$C_2 = \frac{3.4 \times \varepsilon^{-2.6}}{D_P} \quad (19)$$

This closure is particularly relevant when the storage medium consists of gravel, crushed granite, magnetite, or other irregular rock particles.

It should be noted that the conversion of a pressure-drop correlation into the standard *Darcy–Forchheimer* coefficient form is physically consistent only when the original pressure-gradient expression can be separated into a viscous term proportional to the superficial velocity and an inertial term proportional to the square of the superficial velocity. This condition is satisfied for the *Ergun*-type and *Chandra–Willits*-type formulations used above, because their pressure-gradient equations contain explicit linear and quadratic velocity contributions. Therefore, the resulting permeability and inertial resistance coefficients can be interpreted as constant porous-medium inputs, provided that the same definitions of superficial velocity, particle diameter, porosity, and *Reynolds* number are retained.

In contrast, some rock-bed-specific correlations, such as those of *Allen et al.* [16], are expressed in friction-factor form with weak *Reynolds*-number power-law dependencies. When such correlations are rewritten as a pressure-gradient term, the nonlinear resistance contribution does not necessarily scale exactly with u^2 , as assumed in the classical *Darcy–Forchheimer* source term. Consequently, representing these correlations using a constant inertial resistance coefficient introduces an approximation whose accuracy depends on the selected operating *Reynolds*-number interval. For CFD implementation, the most consistent approach is to impose the original pressure-gradient correlation directly as a velocity-dependent momentum source term when the solver allows it. If the solver requires the standard *Darcy–Forchheimer* form, an effective inertial coefficient should be evaluated at a representative *Reynolds* number or fitted over the expected operating range of the RTES system. This approximation may influence the predicted pressure drop, local airflow distribution, fan power, and thermal-front development, especially when the local velocity field extends outside the calibration interval. Therefore, when rock-bed-specific correlations are converted into *Darcy–Forchheimer* coefficients, the conversion assumptions and the applicable *Reynolds*-number range should be clearly stated, and validation against experimental pressure-drop data is recommended whenever possible.

The continuity equation (mass conservation) may be expressed as follows in light of the airflow's incompressibility (superficial velocity vector is shown by $\mathbf{u}$):

$$\nabla \cdot \mathbf{u} = 0 \quad (20)$$

When a porous material is present, the momentum equation is modified to include *Darcy* and *Forchheimer* resistance terms [51]:

$$\rho_f \frac{D\mathbf{u}}{Dt} = -\nabla P + \mu_f \nabla^2 \mathbf{u} - \left(\frac{\mu_f}{\kappa} \mathbf{u} + C_{inertial} \rho_f |\mathbf{u}| \mathbf{u} \right) \quad (21)$$

where fluid density, pressure, dynamic viscosity, permeability, and the *Forchheimer* coefficient (inertial loss) are represented by ρ_f , p , μ_f , κ , and $C_{inertial}$, respectively.

4.2. Thermal Field Modeling

Concerning the thermal models in the categorizations of the volume-averaged model, there are two different models, including the following:

- Local thermal non-equilibrium (LTNE);
- Local thermal equilibrium (LTE).

LTNE and LTE models are two basic approaches for modeling the interaction between the solid matrix and the fluid phase in heat transport within porous media. The main difference between these models lies in how they handle the temperature distribution within the porous medium, which affects their applicability across different physical scenarios. The LTNE model uses two temperature fields, requiring more detailed information on the heat-transfer features of both phases, whereas the LTE model simplifies this by assuming a single

temperature field. The LTNE model explicitly accounts for heat transfer between the liquid and solid phases, making it suitable for situations with significant interfacial heat-transfer resistance or rapid transient processes. Non-equilibrium models are inherently more complex and computationally intensive because they require solving two coupled energy equations. In contrast, equilibrium models offer a more straightforward, computationally efficient alternative that uses a single energy equation with effective-medium properties.

4.2.1. LTNE Model

Two distinct temperature fields (T_s for the solid phase and T_f for the fluid phase) are produced by this model's assumption that the solid matrix and the fluid phase may have different temperatures at any given moment. This method is essential for effectively simulating situations with large temperature differences between the solid and fluid phases, where sluggish heat transfer rates relative to the heat transport rates within each phase limit the simulation. Two coupled energy equations, one for the solid phase and another for the fluid phase, are solved simultaneously using this model. An interfacial heat-transfer term that simulates heat exchange between the solid and fluid connects these equations. This model is particularly relevant in high-speed flows, rapid heating or cooling processes, and systems with significant phase change, such as packed-bed reactors, geothermal reservoirs, and heat exchangers with large thermal gradients. The assumptions considered for this model are as follows:

- The phases of the solid and fluid are not in thermal equilibrium, so they have separate temperatures.
- The interfacial heat-transfer coefficient, h_{sf} , characterizes heat transfer between the phases.
- Both conductive and convective heat transfer (for the fluid phase) are considered.

The volume-averaged theories of transient single-phase fluid flow inside porous media can be employed to depict fluid flow and heat transfer in a rock bed [58]. The continuity equation is as follows:

$$\frac{\partial(\epsilon \rho_f)}{\partial t} + \nabla \cdot (\epsilon \rho_f \mathbf{u}) = 0 \quad (22)$$

where ϵ is the porosity of the rock bed, and ρ_f is the fluid density. Also, $\mathbf{u}$ is the superficial velocity vector.

The momentum conservation equation is as follows:

$$\frac{\partial(\epsilon \rho_f \mathbf{u})}{\partial t} + \nabla \cdot (\epsilon \rho_f \mathbf{u} \mathbf{u}) = -\epsilon \nabla p + \nabla \cdot (\epsilon \boldsymbol{\tau}) + \rho_f \mathbf{g} + S_p \quad (23)$$

where μ_f is the fluid viscosity, $\mathbf{g}$ is the gravity vector, and $\boldsymbol{\tau}$ is the stress tensor. Equations (22) and (23) assume isotropic porosity and are valid only for single-phase flow. In Equation (23), S_p is the momentum source term used to calculate the fluid pressure drop in porous media. Many studies have been done to calculate this term, but only two famous and widely used models are discussed here: (i) the *Darcy–Forchheimer* extended model (DF model) and (ii) the Wu model.

(i) Darcy–Forchheimer Extended Model (DF Model) [59]

The following definition of the momentum source term is based on the *Darcy–Forchheimer* extended model (DF model):

$$S_p = -\frac{1}{2} \rho_f C_2 |\mathbf{u}| \mathbf{u} - \frac{\mu_f}{\kappa} \mathbf{u} \quad (24)$$

where κ is the permeability of the rock bed. The terms $\frac{\mu_f}{\kappa} \mathbf{u}$ and $\frac{1}{2} \rho_f C_2 |\mathbf{u}| \mathbf{u}$ represent the viscous resistance and inertial forces (momentum resistance) due to pore walls on the fluid. The symbol C_2 represents the inertia resistance term, which might be stated as follows:

$$C_2 = \frac{3.5(1 - \varepsilon)}{\varepsilon^2 \times D_p} \quad (25)$$

where D_p is the particle diameter or equivalent particle diameter of the packed medium.

(ii) Wu's Model [59]

Wu et al. [59] present a momentum source term model to forecast the pressure decrease in porous media based on the simulation and experimental findings:

$$S_P = -\frac{1039 - 1002\varepsilon}{D_p^2} \mu_f \mathbf{u} - \frac{0.5138\varepsilon^{-5.739}}{D_p^2} \rho_f \mathbf{u}^2 \quad (26)$$

Note that Wu's approach is applicable to porous media with a porosity range of $0.66 < \varepsilon < 0.93$ and *Reynolds* number range of $10 < Re_p < 400$. For the solid and fluid sectors, energy equations are derived to account for local thermal non-equilibrium.

Equation for energy conservation in the fluid area of the rock bed:

$$\frac{\partial(\varepsilon \rho_f C_{p,f} T_f)}{\partial t} + \nabla \cdot (\rho_f C_{p,f} \mathbf{u} T_f) = \nabla \cdot (\varepsilon k_f \nabla T_f) + h_{fs} A_{fs} (T_s - T_f) + q_f \quad (27)$$

Equation for energy conservation in the rock bed's solid area:

$$\frac{\partial[(1 - \varepsilon) \rho_s C_{p,s} T_s]}{\partial t} = \nabla \cdot [(1 - \varepsilon) k_s \nabla T_s] + h_{fs} A_{fs} (T_f - T_s) + q_s \quad (28)$$

C_p stands for particular heat. The solid and fluid parts, respectively, are represented by the indexes s and f . The thermal conductivity is denoted by k . Additionally, q_f and q_s stand for the fluid and solid phases' corresponding volumetric heat sources and sinks. Additionally, the heat-transfer coefficient, or h_{sf} , has the following definition:

$$h_{fs} = \frac{k_f}{D_p} Nu_P \quad (29)$$

where Nu_P is the fluid–solid Nusselt number. Wakao et al. [46] used the following correlation to determine the Nu :

$$Nu_P = \left[2 + 1.1 \left(\frac{\rho_f \times u_{\text{superficial}} \times D_p}{\mu_f} \right)^{0.6} \left(\frac{\nu_f}{\alpha_f} \right)^{1/3} \right] \quad (30)$$

Furthermore, A_{sf} is the rock-bed-specific area, defined as follows:

$$A_{fs} = 6 \frac{(1 - \varepsilon)}{D_p} \quad (31)$$

4.2.2. LTE Model

According to this concept, the fluid phase and the solid matrix within the porous medium are always in thermal equilibrium, meaning their temperatures (T) are constant throughout the medium. When heat transfer between the solid and the fluid is sufficiently rapid to maintain a uniform temperature distribution throughout the porous structure, this simplification is appropriate. Using an effective thermal conductivity to account for combined heat transfer between the solid and fluid components, this model requires solv-

ing only one energy equation for the porous medium. This effective thermal conductivity is a weighted average of the thermal conductivities of the solid and fluid phases, often accounting for the porosity and thermal conductivity of each phase. This model works well when there are modest heat fluxes, sluggish fluid movements, or comparable thermal characteristics between the fluid and solid phases. Common uses include natural convection in saturated porous layers, low-speed convective processes in porous insulation, and subterranean heat storage. The following presumptions are taken into account for this model:

- The solid and fluid phases are always in thermal equilibrium, with no temperature difference.
- Effective properties (ρ , C_p , k_{eff}) are used to represent the combined behavior of the solid/fluid phases.
- The model simplifies the analysis by using a single energy equation with an effective thermal conductivity that captures the porous medium's overall heat transfer capability.

The following is the energy equation for the LTE model:

$$\frac{\partial(\varepsilon\rho C_p T)}{\partial t} + \nabla \cdot (\rho C_p \mathbf{u} T) = \nabla \cdot (\varepsilon k_{eff} \nabla T) + q \quad (32)$$

where q denotes volumetric heat sources or sinks and k_{eff} is the effective thermal conductivity, accounting for both the solid matrix and the fluid phase.

Correlations for estimating k_{eff} of porous media are essential for engineers and scientists to predict heat-transfer behavior without resorting to complex, time-consuming microscopic analyses. These correlations typically relate k_{eff} to the thermal conductivities of the solid matrix (k_s) and the fluid (k_f), the porosity (ε), and sometimes other structural characteristics of the porous medium. Here are some of the most commonly used correlations.

Parallel Model [59]

This model assumes heat flow parallel to layers, suitable for highly anisotropic media:

$$k_{eff} = \varepsilon k_f + (1 - \varepsilon) k_s \quad (33)$$

Series Model [59]

This model assumes heat flow perpendicular to layers, applicable to layered media:

$$k_{eff} = \left(\frac{\varepsilon}{k_f} + \frac{1 - \varepsilon}{k_s} \right)^{-1} \quad (34)$$

The parallel model assumes heat flow parallel to the material layers, while the parallel-series model assumes it perpendicular to them. The parallel model is more accurate for layered media with parallel heat flow, and the series model is more suitable for stacked or cross-layered media with perpendicular heat flow. The parallel model tends to provide an upper bound (potentially overestimating) of k_{eff} , while the series model provides a lower bound (potentially underestimating).

Maxwell–Eucken Model [60,61]

For a dilute suspension of spherical particles (or pores), Maxwell derived an expression for k_{eff} :

$$k_{eff} = k_f \left(\frac{k_s + 2k_f - 2\varepsilon(k_s - k_f)}{k_s + 2k_f + \varepsilon(k_s - k_f)} \right) \quad (35)$$

This equation applies particularly to systems in which the solid phase is dispersed in the fluid.

Bruggeman Model [62]

Bruggeman's model is often used for systems with high porosity and where the solid and fluid phases form a continuous network. It is a type of practical medium theory:

$$\frac{k_{eff} - k_f}{k_{eff} + (2/3)k_f} \varepsilon + \frac{k_{eff} - k_s}{k_{eff} + (2/3)k_s} (1 - \varepsilon) = 0 \quad (36)$$

This model is solved iteratively or numerically for k_{eff} .

4.2.3. LTNE/LTE Model Selection Procedure

Beyond their low cost, robustness, and scalability, RTES systems (as thermal batteries) also offer thermal safety advantages over electrochemical batteries. In lithium-ion batteries, thermal runaway is driven by self-accelerating exothermic reactions and may lead to fire or explosion hazards [63,64]. In contrast, high-temperature RTES stores energy as sensible heat in inert rock media and is not governed by electrochemical runaway mechanisms. However, thermal safety and durability remain important at elevated operating temperatures, where non-uniform airflow, local overheating, thermal-front distortion, heat losses, and cyclic degradation of the rock medium may affect system reliability. Therefore, accurate pressure-drop and interphase heat-transfer closures are essential for predicting local temperature distribution and supporting safe operation of high-temperature RTES systems.

Figure 8 presents the algorithmic framework for selecting and applying LTE and LTNE porous-medium models in RTES simulations. The schematic is important because it organizes the complete modelling procedure from the required geometrical, thermophysical, and operating inputs to the calculation of derived parameters, pressure-drop closures, thermal-equilibrium criteria, governing energy formulation, and final performance outputs. In particular, the inclusion of the interphase coupling number (equivalent to a bed-scale heat-transfer NTU), N_{fs} , and the particle *Biot* number, Bi_s , provides a rational basis for deciding whether the simpler LTE assumption is acceptable or an LTNE formulation is required, as dimensionless thermal-equilibrium criteria.

$$N_{fs} = \frac{h_v \times L_{PB}}{\rho_f \times C_{p,f} \times u_{Superficial}} = \frac{6(1 - \varepsilon) \times Nu_p \times k_f \times L_{PB}}{\rho_f \times C_{p,f} \times u_{Superficial} \times D_P^2} \quad (37)$$

$$Bi_s = \frac{h_{fs} \times D_P}{6k_s} \quad (38)$$

where h_v is the volumetric fluid–solid heat-transfer coefficient, L_{PB} is the characteristic length of thermal variation, usually the bed length or thermocline length, $u_{Superficial}$ is the superficial velocity, and $\rho_f \times C_{p,f} \times u_{Superficial}$ represents the fluid's advective heat-capacity flux.

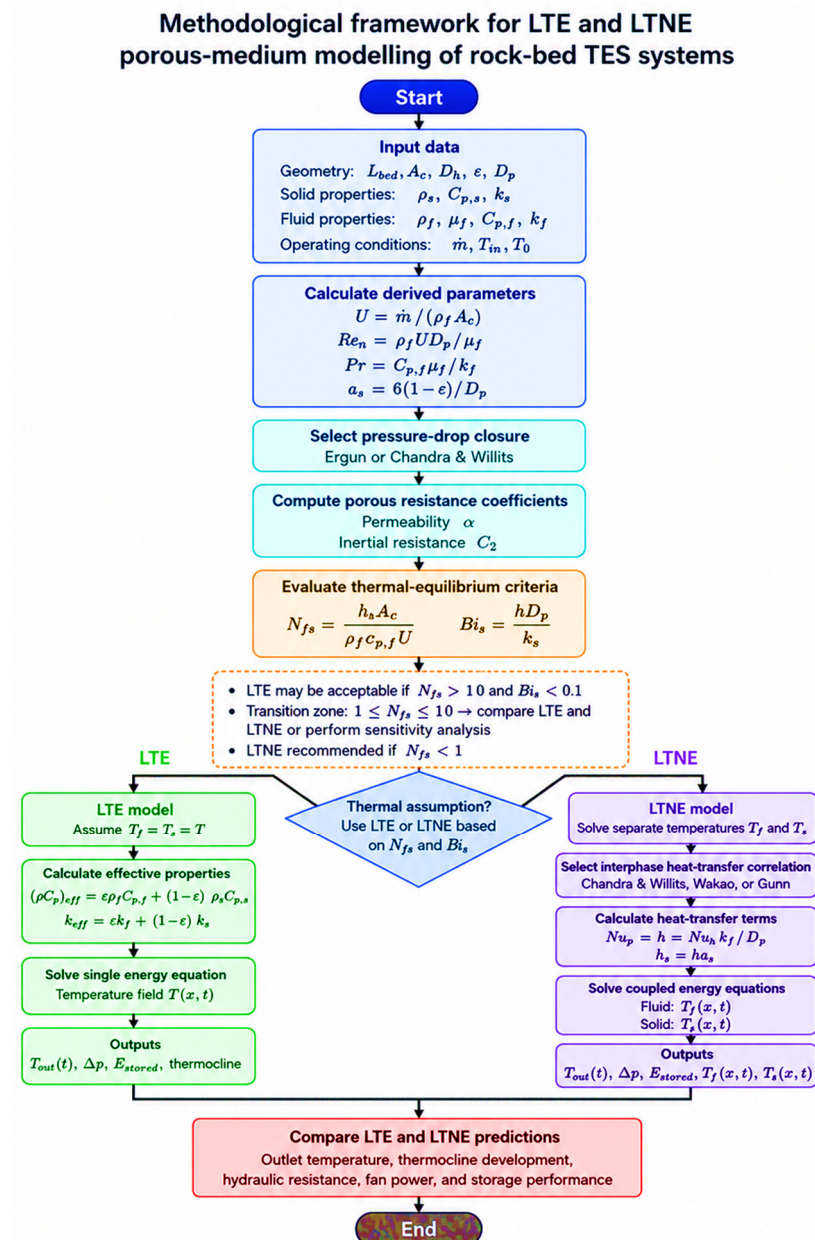


Figure 8. Algorithmic framework for selecting and applying LTE and LTNE porous-medium models for RTES systems.

By separating the LTE and LTNE branches, the figure clarifies how effective properties are used in the single-temperature LTE model, whereas interphase heat-transfer correlations such as *Chandra–Willits*, *Wakao*, or *Gunn* are required in the two-temperature LTNE model. Thus, the schematic provides a structured methodology for comparing outlet temperature, thermocline development, pressure drop, fan power, stored energy, and overall storage performance under different thermal-equilibrium assumptions.

Figure 8 presents the proposed methodological workflow for continuum porous-medium modelling of RTES systems using either the LTE or LTNE formulation. The procedure starts with the required input data, including bed geometry, porosity, particle diameter, solid and fluid thermophysical properties, and operating conditions such as mass flow rate and inlet temperature. These inputs are then used to calculate the main derived parameters, including superficial velocity, particle *Reynolds* number, *Prandtl* number, and specific interfacial area. After selecting an appropriate pressure-drop closure, such as *Ergun* [23–25] or *Chandra–Willits* [15], the porous resistance coefficients, namely permeability

and inertial resistance, are determined for the momentum equation. The flowchart then introduces two dimensionless criteria, namely the interphase thermal coupling number, N_{fs} (Equation (37)), and the particle *Biot* number, Bi_s (Equation (38)), to guide the selection between LTE and LTNE. It should be emphasized that the limits based on the N_{fs} are intended as practical screening criteria rather than universal experimentally validated thresholds. The interphase thermal coupling number can be interpreted as a bed-scale heat-transfer number that compares the volumetric fluid–solid heat-exchange capacity to the fluid’s advective heat-capacity flux. Therefore, small values of the N_{fs} indicate weak interphase coupling and a higher probability of fluid–solid temperature differences. In contrast, large values indicate stronger thermal coupling between the air and rock phases. In the present framework, $N_{fs} < 1$ is considered a conservative indication that LTNE modelling should be used. Conversely, $N_{fs} > 10$, together with $Bi_s < 0.1$, suggests that the LTE assumption may be acceptable, as interphase exchange is strong and the particles can be treated as internally uniform. The intermediate range, $1 \leq N_{fs} \leq 10$, should be regarded as a transition or uncertainty interval; for systems falling in this range, both LTE and LTNE simulations, or a sensitivity analysis on the interphase heat-transfer coefficient, are recommended before selecting the final model. This interpretation is especially important for RTES systems because N_{fs} depends on particle diameter, porosity, bed length or thermocline length, air velocity, fluid properties, and the selected heat-transfer correlation. In the LTE formulation, a single temperature field is solved using effective heat capacity and thermal conductivity. In contrast, in the LTNE formulation, separate fluid and solid energy equations are solved and coupled through an interphase heat-transfer coefficient obtained from correlations such as those of *Chandra–Willits* [15], *Wakao et al.* [46], or *Gunn* [45]. Finally, the outputs of both approaches, including outlet temperature, pressure drop, stored energy, thermocline development, fan power, and overall storage performance, are compared to assess the influence of the thermal-equilibrium assumption on RTES predictions. Therefore, the LTE/LTNE decision should be supported by system-specific validation whenever transient experimental data are available.

For example, consider a representative air–RTES case with $\varepsilon = 0.4$, $D_p = 20$ mm, $L_{PB} = 1$ m, $u_{superficial} = 0.2$ m·s^{−1}, $\rho_f = 1.2$ kg·m^{−3}, $C_{p,f} = 1005$ J·kg^{−1}·K^{−1}, $\mu_f = 1.85 \times 10^{-5}$ Pa·s, $k_f = 0.026$ W·m^{−1}·K^{−1}, and $k_s = 2.5$ W·m^{−1}·K^{−1}. Under these conditions, the particle *Reynolds* number is approximately $Re_p = 432.4$, which falls within the validity range of the *Chandra–Willits* correlation [15] reported in Table 3. Using the *Chandra–Willits* expression, $Nu_p = 1.45 \times Re_p^{0.7} / [6 \times (1 - \varepsilon)^{0.3}]$, gives an Nu_p around 19.8. Therefore, the particle–fluid heat-transfer coefficient becomes $h_{sf} = Nu_p \times k_f / D_p$, which is around 25.8 W·m^{−2}·K^{−1}. The corresponding specific interfacial area is $A_{fs} = 6 \times (1 - \varepsilon) / D_p$, equal to 180 m^{−1}, giving a volumetric heat-transfer coefficient of $h_v = h_{sf} \times A_{fs}$ around 4.64×10^3 W·m^{−3}·K^{−1}. Substituting these values into Equations (37) and (38) gives an N_{fs} of around 19.2 and Bi_s of around 0.034. Since $N_{fs} > 10$ and $Bi_s < 0.1$, the LTE assumption may be acceptable as a first modelling approximation for this case. However, if larger particles, higher airflow rates, weaker interphase heat transfer, or stronger thermal transients are involved, the system may fall into the transition or LTNE range. Therefore, these criteria should be interpreted as screening indicators rather than universal thresholds, and the final model selection should preferably be validated against experimental outlet-temperature evolution, thermocline development, pressure-drop data, or stored/released energy measurements.

5. Conclusions

The present review provides a systematic evaluation of continuum porous-medium CFD modelling of rock-bed thermal energy storage systems by linking the physical behavior of packed rocks with the closure correlations required for practical simulations. First,

the review distinguishes between pore-scale and volume-averaged modelling approaches and discusses why continuum models are preferred for engineering-scale RTES simulations. The hydraulic aspects are then examined using pressure-drop and friction-factor correlations, followed by the thermal aspects using particle-to-fluid heat-transfer and Nu_p -based correlations. Finally, a methodological framework is proposed for applying LTE and LTNE formulations, including the required inputs, governing assumptions, closure models, and dimensionless criteria for selecting an appropriate thermal model.

- The analysis of friction-factor correlations indicates that hydraulic resistance in packed beds is strongly affected by porosity, particle morphology, surface roughness, packing arrangement, bed-to-particle diameter ratio, and flow regime. Classical correlations, such as *Ergun* (1952), remain useful as baseline closures; however, they may not be universally reliable for natural or crushed rock beds because irregular particles introduce additional resistance that is not fully captured by idealized spherical-bed assumptions. Rock-bed-specific correlations, such as those of *Chandra–Willits* (1981) and *Allen et al.* (2015), are more physically representative for RTES applications, although their validity ranges are relatively narrower. More general correlations, such as *Macdonald*-type formulations (1979), are applicable across a broader range of packed-bed conditions because they account for porosity, roughness, and inertial effects more comprehensively. Nevertheless, for practical RTES modelling, the final selection of a friction-factor correlation should be based on the similarity between the target rock bed and the experimental conditions under which the correlation was developed.
- The comparison of particle Nusselt-number correlations suggests that the predicted interphase heat transfer can vary significantly depending on the selected closure. General correlations, such as that of *Wakao et al.* (1979), are widely used as benchmarks and are useful for continuum modelling; however, they do not explicitly account for porosity or particle morphology. The *Chandra–Willits* (1981) correlation is particularly applicable to air–RTES systems because it was developed for rock beds and provides a volumetric heat-transfer coefficient. However, its validity range is relatively limited. The *Gunn* (1978) correlation is also useful as a general benchmark for parametric CFD studies because it explicitly includes porosity and covers a broad range of packed-bed conditions. Nevertheless, it should not be interpreted as universally superior for natural or crushed rock beds, because it does not explicitly account for particle morphology, angularity, surface roughness, or polydispersity. Therefore, *Gunn* (1978) is most suitable when the objective is to perform generalized sensitivity analyses on Re_p and porosity, particularly when rock-specific heat-transfer data or experimental calibration are not available. In contrast, *Chandra–Willits* (1981) should be preferred for applications with operating conditions close to those of low-temperature air–RTES. For irregular natural or crushed rocks, rock-bed-specific or pore-scale-derived correlations should be preferred whenever their validity ranges and experimental conditions are close to the target RTES system. Future work should focus on developing and validating morphology-corrected heat-transfer closures to improve the applicability of general correlations to natural rock beds.
- The selection between LTE and LTNE formulations is also critical because it determines whether the air and solid phases are forced to share a single temperature or allowed to develop separate thermal fields. The LTE may be acceptable when interphase heat transfer is sufficiently strong, and the fluid and rock temperatures remain locally close; however, the LTNE is more appropriate during transient charging and discharging, when thermal fronts move through the bed and finite air–solid temperature differences can occur.

Future work should focus on developing and validating closure correlations for realistic RTES systems composed of irregular, angular, rough, and polydisperse particles. Additional experimental data are needed for different rock types, porosity ranges, bed geometries, airflow configurations, and cyclic charging/discharging conditions. Particle-resolved CFD and pore-scale simulations can also support the development of improved continuum closures by quantifying local velocity fields, contact effects, interfacial area, and thermal non-equilibrium behavior. Future studies should also incorporate hydraulic resistance, heat-transfer closure uncertainty, wall heat loss, thermal dispersion, and long-term cyclic degradation into integrated CFD frameworks. Such developments will improve the reliability of RTES design and support the optimization of rock-bed thermal batteries for buildings, greenhouses, and solar-assisted energy systems.

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Nomenclature

Symbol		Unit
A	Cross-sectional area	m ²
A _c	Empty-bed cross-sectional area	m ²
A _p	External surface area of a particle	m ²
A _{sf}	Solid–fluid interfacial area	m ²
a _s	Specific solid–fluid interfacial area per unit bed volume	m ^{−1}
Bi	<i>Biot</i> number	-
C _p	Specific heat capacity	J·kg ^{−1} ·K ^{−1}
D	Bed diameter or characteristic bed dimension	m
D _H	Hydraulic diameter	m
D _v , D _{eq}	Equivalent-volume particle diameter	m

D_{sv}	Surface-volume particle diameter	m
D_{32}	Sauter mean diameter	m
E	Stored or released thermal energy	J
f	Packed-bed friction factor	-
h	Particle–fluid heat-transfer coefficient	$W \cdot m^{-2} \cdot K^{-1}$
h_v	Volumetric heat-transfer coefficient	$W \cdot m^{-3} \cdot K^{-1}$
i	Index of the Reynolds-number point	-
k	Thermal conductivity	$W \cdot m^{-1} \cdot K^{-1}$
L	Bed length or packed-bed height	m
m	Mass	kg
$\dot{m}$	Mass flow rate	$kg \cdot s^{-1}$
N	Number of Reynolds-number points used in the weighted statistical analysis	-
Nu_p	Particle Nusselt number	-
Nu_V	Volumetric or modified Nusselt number	-
p	Pressure	Pa
Pr	Prandtl number	-
q	Heat flux	$W \cdot m^{-2}$
$\dot{Q}$	Heat-transfer rate	W
Re_p	Particle Reynolds number	-
T	Temperature	K or °C
t	Time	s
u	Velocity	$m \cdot s^{-1}$
V	Volume	m^3
x, y, z	Cartesian coordinates	m

Greek Symbol

α	Thermal diffusivity	$m^2 \cdot s^{-1}$
β	Empirical coefficient or thermal-offset parameter	- or K
ε	Bed porosity	-
μ	Dynamic viscosity	Pa·s
ν	Kinematic viscosity	$m^2 \cdot s^{-1}$
ρ	Density	$kg \cdot m^{-3}$
τ	Tortuosity	-
ϕ	Shape factor or sphericity	-
ψ	Particle sphericity	-
κ	Permeability	-
δ_i	Relative deviation of the i -th correlation value from the benchmark	%
$\bar{\delta}_w$	Weighted mean relative deviation	%
ω_i	Weighting factor assigned to the i -th Reynolds-number point	-

Subscript

0	Reference
avg	Average
b	Bed
eff	Effective
eq	Equivalent quantity
f	Fluid phase
i, in	Inlet or particle index
m	Modified
max/min	Maximum/minimum value
o, out	Outlet or test-section diameter, depending on context
P	Particle
PB	Packed bed

s	Solid phase
sf	Solid–fluid interface
v	Volume-equivalent quantity
w	Wall
Abbreviation	
CFD	Computational Fluid Dynamics
HTF	Heat Transfer Fluid
LTE	Local Thermal Equilibrium
LTNE	Local Thermal Non-Equilibrium
PMM	Porous-Media Model
REV	Representative Elementary Volume
RTES	Rock-bed Thermal Energy Storage
TES	Thermal Energy Storage
VAM	Volume Averaging Method
WMAD	Weighted Mean Absolute Deviation
WRMSD	Weighted Root-Mean-Square Deviation

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