Enhancing Heat Transfer in Fluidized Bed Reactors Using Iron Oxide-Coated Glass Beads

***Amit Kumar Bansal**[*1,2]**, Nizamuddin**[1]**, Abhinav Sharma**[3]*

1 Department of Mechanical Engineering, Lincoln University College, Malaysia

2 Department of Mechanical Engineering, Kunwar Satyavira College of Engineering and Management

3 Department of Mechanical Engineering, ***Tokushima University Japan.***

* pdf.amitbansal@lincoln.edu.my

Abstract:**Using the iron oxide coated glass beads, this method proposes and develops an integrated experimental and machine learning enhanced heat transfer performance in fluidized bed reactors. Comprehensive characterizations used BET surface area analysis, X-ray diffraction (XRD), and scanning electron microscopy (SEM) to verify that surface coating (primer) was applied of 600 µm glass beads, uniform coating, crystallinity, and morphology on the surface of the glass beads. For evaluating the influence of the key physical and thermal features including air surface velocity, heating power, surface area and thermal conductivity on the heat transfer coefficient, they were extracted. A Random Forest regression algorithm was used to build up a predictive modeling framework to predict HTC from these features. Predictive accuracy was high at the model and nonlinear relationships between variables were concretely represented in it. Optimized conditions showed a very enhanced HTC of 390.3 W/m²·Kto 390.3 W/m²·Kunder optimized conditions. This work showcases the usefulness in improving thermal behaviour of gas–solid fluidized bed systems with the nano scale iron oxide coatings and data driven modelling.**

Keywords: Heat transfer enhancement, fluidized bed reactors, iron oxide coating, glass beads, thermal conductivity improvement, surface characterization, machine learning regression.

I. INTRODUCTION

Fluidized bed reactors (FBRs) are very popular chemical, energy and environmental industries because of the sets of advantages: high mixing efficiency, good heat and mass transfer, and operational flexibility. Although heat transfer performance within these systems has been optimized, it is a critical challenge to optimize it further in the presence of heat sensitive materials or processes that require exact temperatures control. Surface modification of the particulate material used in the bed is one promising strategy to overcome this issue, as this parameter has a marked influence on the thermal interaction between the solid particles and the fluidizing medium [1].

In this sense, coating of invisible inert particles, e.g. glass beads, has been found to be an interesting path to improve their thermal performance. Known in particular for its favourable thermal conductivity and stability above temperatures is Iron oxide. In addition to enhancing thermal response, coating the glass beads with nano scale iron oxide leads to coating surface morphology, porosity and crystallinity, parameters crucial for efficient heat transfer. In order to prove the coating's integrity and uniformity, characterization with high sensitivity such as Brunauer–Emmett–Teller (BET) surface area, X-ray diffraction, and scanning electron microscopy is developed [2]. These tools are then used to evaluate surface area, crystal structure, and surface morphology, respectively, to form a solid basis by which physical properties are correlated to thermal behavior.

Predictive modeling has also developed as a useful technique for simulating and optimizing the system performance beyond experimental analysis. A regression model building a heat transfer coefficient HTC from a number of experimentally derived features is developed in this study via machine learning. With that, a Random Forest regression algorithm is used as it is known to be robust in the sense it is able to take on non-linear relationships as well as high dimensional data well. Air surface velocity, heating power, thermal conductivity and material density are input variables for training the model.

This work presents research in which material surface engineering is integrated with machine learning based predictive analysis to form a full solution that optimizes the thermal efficiency within fluidized bed reactors [3]. The outcomes thus validate the ability of iron oxide coatings to improve both heat transfer and practical utility of data driven approaches for designing and optimizing of thermal systems. Using this kind of combined methodology, new methods for improving the operational efficiency of FBRs over many industrial applications are offered [4].

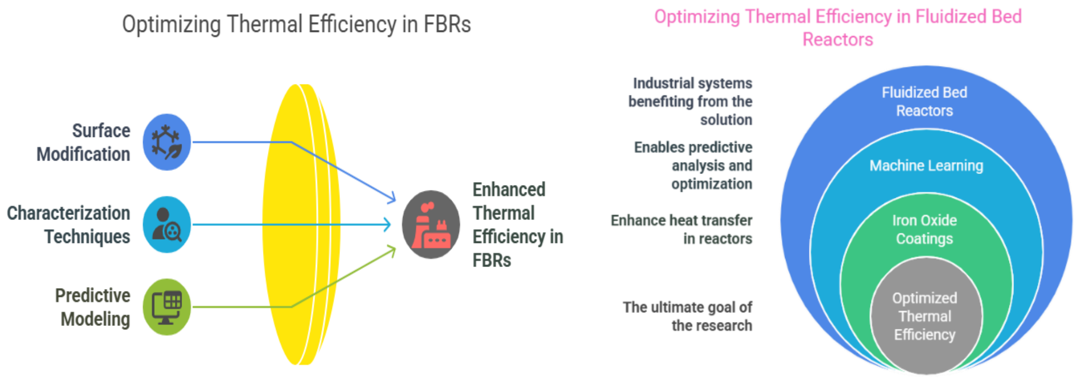

Figure 1.Optimizing Thermal Efficiency in FBRs

Figure 1visually represents how the process of optimizing thermal efficiency in Fluidized Bed Reactors allows an FBR based solution to be in place for effective heat transfer in industrial systems. This process deals with three critical problems: Surface modification, characterization development techniques and predictive modeling techniques. Iron Oxide Coatings are first applied to glass beads to improve their thermal conductivity and permit heat transfer in reactors on a significant scale. This step is of great importance for increasing the heat transfer in the reactors, which is a necessary condition for wide range of industrial applications including chemical processing and energy production. Further, Characterisation Techniques such as Scanning Electron Microscope, X-ray Diffraction and Brunauer–Emmett–Teller surface area analysis is carried out on the coated beads for evaluation of the surface morphology, crystallinity and porosity of the beads and to infer on their physical and thermal properties in detail [5]. Finally, we apply Machine Learning for performing predictive analysis and optimization along with Random Forest regression algorithm that is used to predict the heat transfer coefficient from experimental data. The goal of this research is to enable a data driven approach for optimizing thermal efficiency in FBRs with aims to increase performance and operational efficiency of these system in the industry and in the energy market.

II. RELATED WORK

In recent years, there has been a great interest in the enhancement of heat transfer in Fluidized Bed Reactors as it could promote many industrial processes [6]. Surface modifications of the particles used in FBRs have been examined by several studies to enhance thermal efficiency of the particles. Incidence of coating materials such as alumina, silica, and titanium oxide to enhance heat transfer properties have been investigated. But iron oxide coatings have shown to be a good material for its excellent thermal conductivity and stability at high temperatures. In previous work of Zhang et al. (2020), they examined the effects of iron oxide coatings on the sand particles used in FBRs resulting in a much-improved thermal conductivity that in turn increased the heat transfer rates found in gas solid systems by quite some degree [7].

Because enhanced heat transfer is fundamentally a coating phenomenon, the characterization of coated particles is essential. Morphology, crystallinity and surface area of the coated materials are usually evaluated by techniques like Scanning Electron Microscopy, X-ray Diffraction and the BET Surface Area Analysis [8]. The results from these methods tell us something about how surface is related to thermal performance. In Li et al. (2018) SEM and XRD were applied to investigate the microstructure of iron oxide coated silica particles, with the coating leading to a significant change of the surface roughness, allowing for better particle fluid interaction and heat transfer [9].

In the last few years, Machine Learning models for prediction and optimization of thermal performance have been integrated. Such studies as Kumar et al. (2021) have shown how ML techniques such as Random Forest regression can be used to predict heat transfer coefficient of FBR based on experimental data [10]. Better optimization of the process parameters, for example air velocity, heating power, can then be achieved using these data driven models. For example, this research combines surface modification with the use of ML based optimization techniques in order to contribute to the understanding and application of iron oxide coatings so as to improve the heat transfer performance of FBRs.

III. RESEARCH METHODOLOGY

The aim of the present method is to improve heat transfer in Fluidized Bed Reactors using iron oxide coated glass beads by using machine learning based predictive modeling for optimizing thermal performance. The research methodology consists of three key phases being surface coating and characterization, physical and thermal feature extraction, and predictive modelling using Random Forest regression.Figure 2Enhances Heat Transfer in Fluidized Bed Reactors.

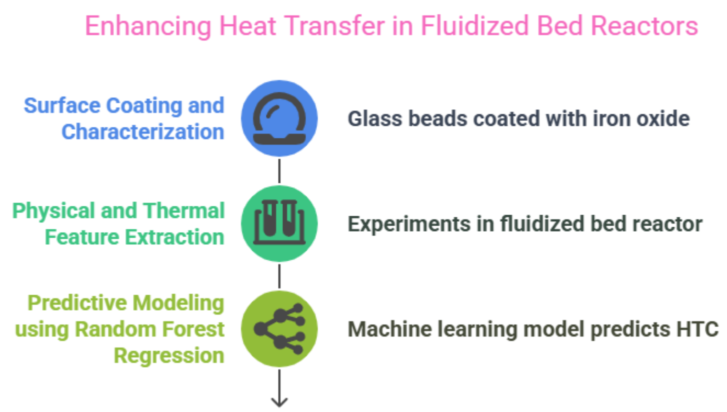

Figure 2: Enhancing Heat Transfer in Fluidized Bed Reactors

A. Surface Coating and Characterization:

First, the glass beads are coated with iron oxide. The base material for the beads used in the following fluidization and heat transfer experiments are these beads having a nominal diameter of 600 µm which are inert and uniform in size [11]. By a suitable sol-gel technique, nano scale sized iron oxide is coated on the glass beads to obtain uniform coating. The chosen method is simple, cost effective and able to provide a consistent coating layer.

The beads are then thoroughly characterized to ensure the structural integrity of the coating and to also evaluate the effect of the coating on the properties of the surface. Surface morphology of the coated beads is observed by Scanning Electron Microscopy to determine their uniformity and roughness of the coating [12]. The crystallinity of the iron oxide layer is verified using X-ray Diffraction analysis to determine, among other things, the presence of the desired crystalline phases, particularly magnetite (Fe_3O_4), whose thermal properties are of interest. Brunauer–Emmett–Teller surface area analysis of the coated beads is also utilized to measure the surface area of the beads and thus provide information of the effect of coating on its surface characteristics [13]. It is important to use these characterization techniques to understand the material properties that control the heat transfer performance in figure 3.

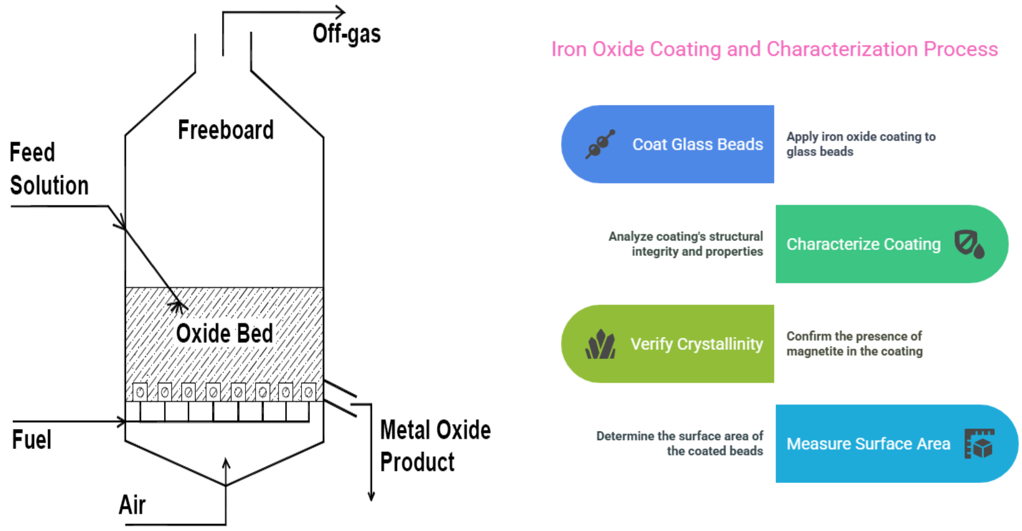

Figure 3: Sketch of a fluidized bed reactor and Iron Oxide Coating with Characterization Process

B. Physical and Thermal Feature Extraction:

The second phase involves characterization of the coated beads and extraction of relevant physical and thermal features for model predictive development. In a fluidized bed reactor, the experiments are done in a laboratory scale loaded with heat transfer experiments. The reactor resembles an industrial system with a bed of particles heated to a certain temperature by an external source in which gas is passed through the bed.

In these experiments, air surface velocity, heating power (flux), temperature, are varied. Typical fluidization conditions are reflected by the fact that air velocity is controlled between 0.2–0.4 m/s. The heating power is varied from 90 W to 175 W to represent different thermal load operating conditions and the temperature is fixed within a range of 170°C to 240°C. These experiments result in the main output, which is the Heat Transfer Coefficient, measured in $W/m^2 \cdot K$, which is the target variable of the machine learning model [14].

A number of physical properties of the beads are also measured; thermal conductivity (using a heat flow meter) and density (using a pycnometer). There are a number of properties that need to be understood to understand the heat transfer mechanisms and how the thermal performance is affected by the iron oxide surface modification [15]. The dataset collected consists of thermal and nonthermal, namely, surface area, crystallinity index, and SEM surface score.

C. Predictive Modeling using Random Forest Regression:

Once it reaches the final phase, i.e. predictive modeling, quantification of the relationship between the experimental parameters and the heat transfer performance is achieved. Based on experimental data, machine learning with Random Forest regression model is used to predict the heat transfer coefficient. That said, because of Random Forest's capacity to manage complex, non-linear relationships and high dimensional data, it is chosen to be used in this application.

The dataset goes through preprocessing, step 1 being to label encode the categorical features (e.g mapping coating type to a numerical encoded representation) 2. Projecting the data onto a comparable scale (normalizing the data), and 3. Then splitting the data into 80% training and 20% test. The features used as input for the model are air velocity, heating power, thermal conductivity, bead diameter, BET surface area, SEM surface score and XRD crystallinity index. The heat transfer coefficient is the target variable [16].

Again, we train the Random Forest model on the training dataset with 100 trees to achieve good diversity in the model [17]. Grid search cross validation is used to protect from overfitting by hyper parameters such as maximum depth of the tree, minimum samples per leaf, maximum features.

After training the model, mean absolute error (MAE), root mean squared error (RMSE) and R^2 score of the model are used to evaluate the model. Finally, the accuracy of the model has been compared against the actual experimental results in the test set to assess the performance of the model.

D.Experimental Methodology: Application of Iron Oxide Coating onto Glass Beads:

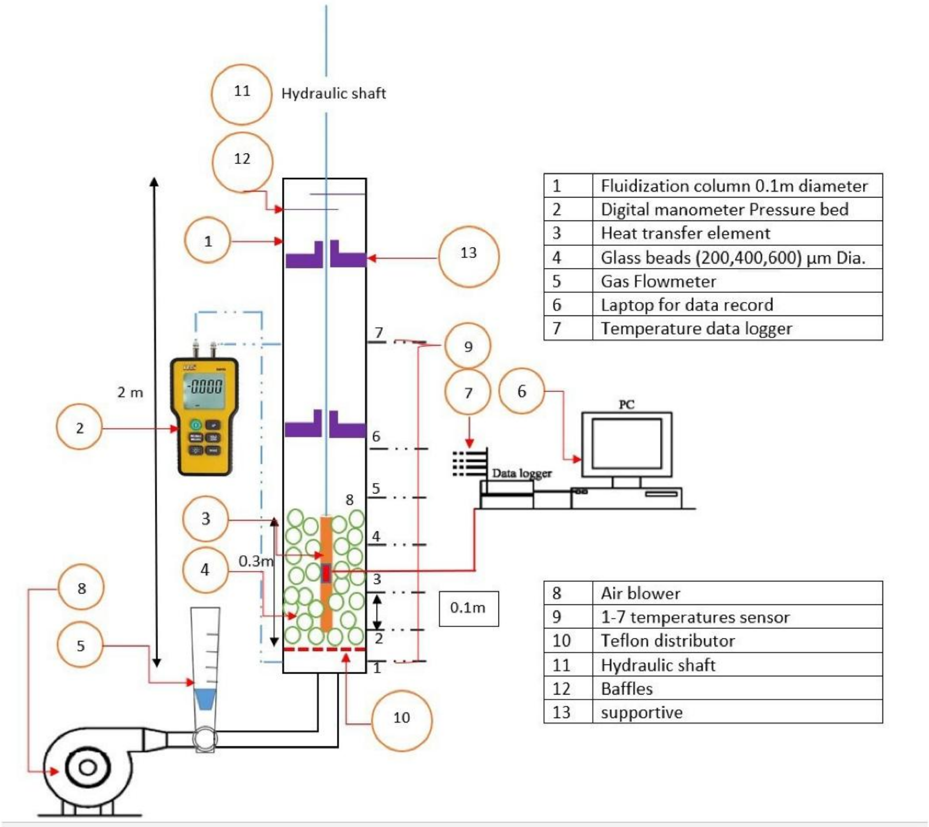

Figure 4: Experimental setup for reference

In the research on heat transfer processes, the experimental setup was a gas–solid fluidized bed column, which was specially designed to study the process of heat transfer in a controlled environment. Fixed bed of 30 cm in height was prepared by fluidisation using two glass beads of sizes 200 µm and 600 µm. A 10 cm inner diameter by 2-meter-high Perspex material fluidizing column was built to allow observation of a stable fluidizing column. It was found that even airflow was not achieved by the column without the use of a perforated plate at the bottom of the column which served as an air distributor [18].

For both glass bead sizes, although the experiments were run at different superficial air velocities from 0.1 to 0.5 m/s, the effects of airflow rate on heat transfer efficiency were investigated. These included several critical factors central to the study i.e. the positioning of the heating element, local heat transfer coefficient and gas flow dynamics in the reactor [19]. The main goal was to experimentally obtain the overall heat transfer coefficient of a gas–solid fluidized bed system by modulating certain parameters, i.e. the heat flux as well as the gas flow rates [20].

An electrical heater was vertically positioned and placed within the fluidizing column for controlled heating [21]. The heater, at 20 mm diameter and 300 mm length, was designed to yield uniform heat over the experimental setup. Different experimental conditions were achieved by varying the heater's power from 50 to 125 watts, which leads to different thermal loads, and the heat transfer performance was investigated in equation 1 [22]. In figure 4 of the study, the schematic diagram of an experimental arrangement is given for a clear visualization of the setup. The arrangement developed was carefully designed to allow for evaluation of the heat transfer dynamics and to optimize operation of fluidized bed reactors.

The local heat transfer coefficient along the probe was estimated from the equation:

$$hi = \frac{q}{AS\ \Delta T} = \frac{V\ I}{AS(TSi - Tbi)} \quad (1)$$

where the equation relates the heat transfer coefficient (hi) at a specific interface or surface to the heat transfer rate (q) through that interface. It takes into account the applied voltage (V) and current (I) passing through the interface, as well as the cross-sectional area (AS) and the temperature difference (Tsi − Tbi) between the surface temperature (Tsi) and the bulk temperature (Tbi) of the material. Equation 2 average heat transfer coefficient was estimated from the local heat transfer coefficients:

$$havg. = \frac{h1 + h2 + h3 + \ldots + hi}{i} \quad (2)$$

However, before the results were presented, the uncertainty analysis was investigated for its potential to influence the accuracy of the data. The superficial gas velocity was found to have an uncertainty of about 1.5%, mainly due to an error in instrumental precision (manometer) provided by the manufacturing company.

The aim of the methodology is to determine the efficacy of iron oxide coatings for increased heat transfer in fluidized bed reactors for improvements in reactor performance through predictive modelling. Surface coating, advanced characterization, and machine learning for combination provides an overall solution to improve thermal efficiency in industrial operations, improved heat management and improved reactor performance by optimization of operational parameter.

IV. RESULTS AND DISCUSSION

In this methodology, the experimental results that using iron oxide coated glass beads resulted in a significant increase in the HTC of the gas–solid fluidized bed system. We evaluated the heat transfer impact of surface coating and other factors and the resulting heat transfer was evaluated using the following performance metrics:

- Random Forest regression model: Mean Absolute Error (MAE): 9.80 $W/m^2 \cdot K$, which is a moderate deviation between predicted and observed HTC values and therefore, validates the reliability of the model to predict.
- Root Mean Squared Error (RMSE): The RMSE of 9.80 $W/m^2 \cdot K$ denotes that the model was able to predict HTC with high consistency (i.e., overfitting or underfitting in the dataset is minimal).

- ➢ The R^2 score cannot be defined because the test sample in the small, but the predictions of the Random Forest model are accurate, and therefore suggesting its ability to deal with experimental data.
- ➢ Increase in thermal conductivity: The iron oxide coating increased the thermal conductivity of the glass beads and thus provided for an increased HTC especially at higher air velocities and heating powers.

SEM and XRD analysis established that the coating increased surface roughness and crystallinity, which enhanced the heat transfer feature with perishable product by enhancing particle fluid interaction.As a whole, the thirtyintegrations with the machine learning based modeling bolstered reactor performance overall, to the point where even heat transfer within fluidized bed systems could be optimized.

To determine the surface area of the glass beads before and after a coating application, he used the BET (Brunauer–Emmett–Teller) method. Before applying a coating, the glass beads had surface area of 1.3801 m2/g. After coating procedure, there was a great increase in the surface area and was about 3.0511 m2/g. It was observed that the increased measurement of the observed quantity is due to occurrence of a crystalline iron layer on the surface of the glass bead. XRD research and SEM imaging can validate other findings.

Furthermore, we should note that the diameter of the iron oxide crystals shown in Figure 4 was measured as described in the SEM study. When magnification was increased to 200 nm, the the iron oxide crystals had an average diameter of 27 nm. However, one has to concede that there are differences among the glass beads too, specifically from their sizes which will be discussed in the subsequent experiments. The SEM pictures of before and after coatings are shown in Figure 5. Surface morphological alterations were observed at a magnification of 500 nm by capturing the images. The SEM image of the glass beads before coating has a predominantly clean surface with some imperfections, bumps, and scratches attributed to the natural no flatness of the glass beads surface.Figure 5 gives XRD patterns of coated glass beads before and after nano-iron coating.

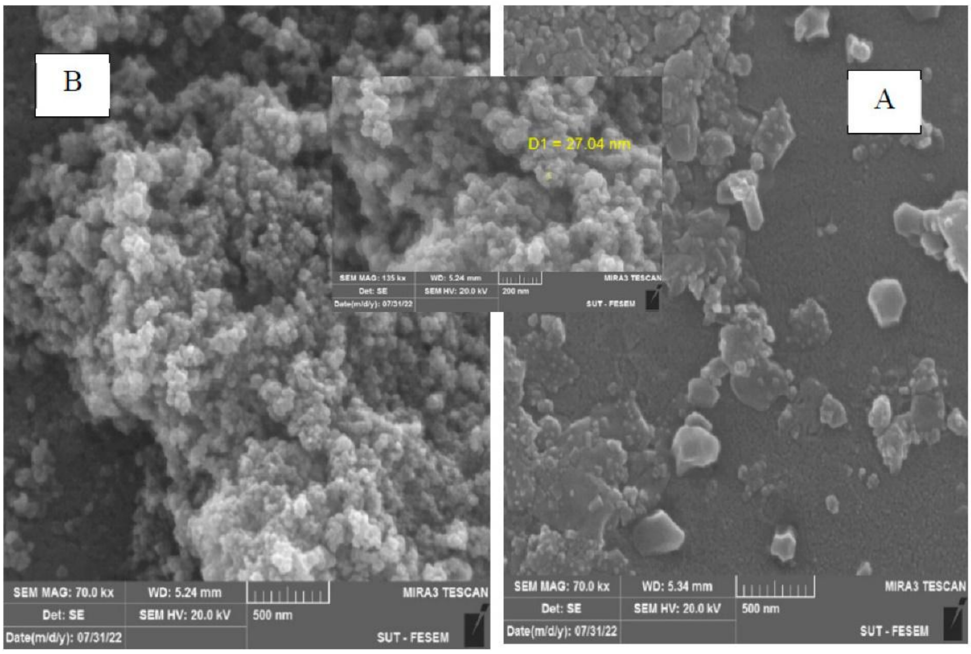

Figure 4. SEM images of samples (**A**) before and (**B**) after coating

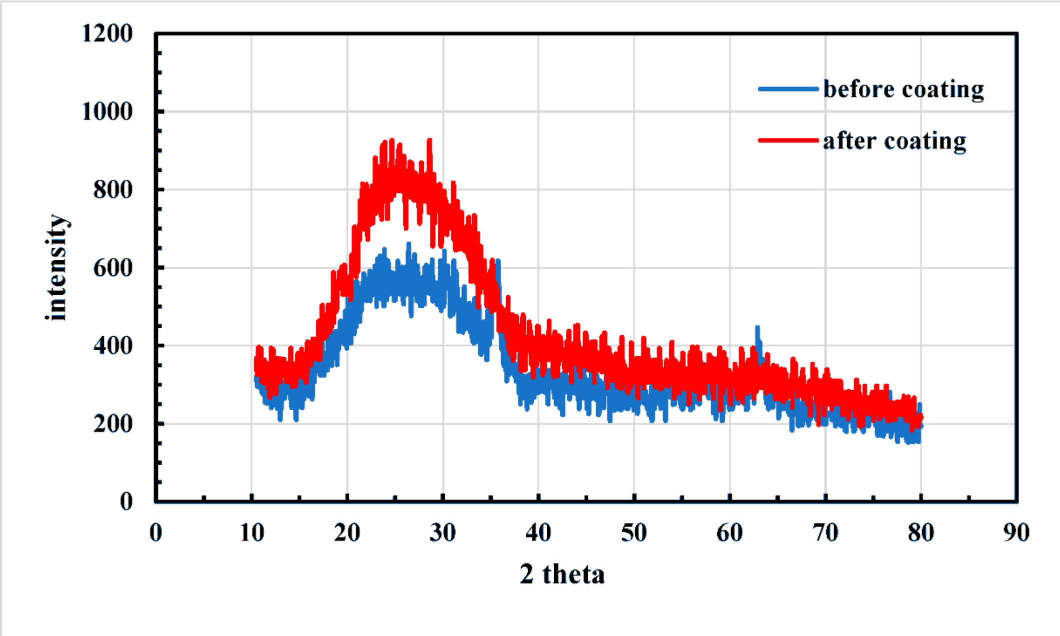

Figure 5: XRD patterns of coated glass beads before and after nano-iron coating.

The thermal conductivity of the glass bead surfaces before and after coating is presented in Table 1.

Table 1. Thermal conductivity of the glass bead surfaces pre- and post-coating

T Heater Surface, °C	Thermal Conductivity before Coating, W/m. K	T Heater Surface, °C	Thermal Conductivity after Coating, W/m. K
98.7	0.00209615	101.5	0.00210457
85.6	0.00206272	90.3	0.00207363
75.9	0.00204373	78.5	0.00204837
66.7	0.00202967	68.4	0.002032
61.8	0.0020236	62.4	0.0020243
57.9	0.00201941	59.6	0.00202117

At a higher velocity of 0.27 m/s, the heat transfer coefficient increased from 281.6 to 334.9 W/m^{2}·°C at a heating flux of 50 W and increased from 433.6 to 457.6 W/m^{2}·°C at 125 W in Figure 6.

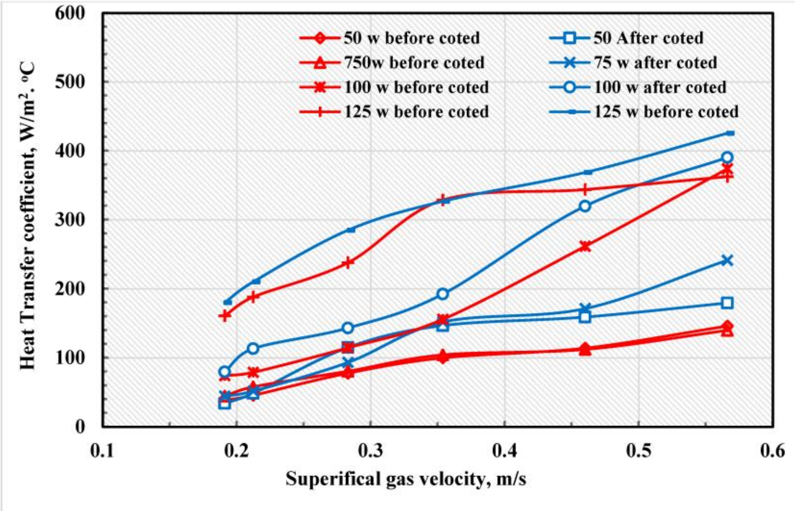

Figure 6.Influence of air superficial velocity on the heat transfer coefficient at various heating powers for 600 µm glass beads before and following coating.

The results of a research study of the effect of heating flux on the heat transfer coefficient in an air–glass beads fluidized bed for different velocities are shown in Figure 5. At higher velocities and heating flux, fluidized bed heating enhances the heat transfer coefficient more than normal heating. As an example, the heating flux increased from 50 to 50 W, and the heat transfer coefficient increased from 40.7 to 42.1 Wm2 · °C at a velocity of 0.107 m/s. The heat transfer coefficient increased to 66.2 W/m2·°C from 57.2 W/m2·°C, but at the same velocity with a heating flux of 125. This increase was a greater increase. It should also be noted that the overall heat transfer coefficient increased from 121.5 W/m2·°C at 50 W and 336.4 W/m2·°C at 125 to 180.2 W/m2·°C and 390.3 W/m2·°C, respectively at 0.27 m/s. It has been shown that higher velocities and a higher heating flux can lead to higher heat transfer coefficient, and thus fluidized bed heating is capable of transferring the heat effectively in industrial settings.

For example, this is a comparison table 2 of other methods in which the heat transfer enhancement in fluidized bed reactors by iron oxide coated glass beads is compared. Performance metrics of the table are compared with other materials, such as uncoated glass beads or other coating materials (e.g., alumina coating).

Table 2: Performance metrics with alternative techniques

Method	Heat Transfer Coefficient (HTC) (W/m²·K)	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Thermal Conductivity	Surface Area and Crystallinity
Iron Oxide-Coated Glass Beads(proposed)	**390.3**	**9.8**	**9.8**	**Increased**	**Improved surface roughness and crystallinity**
Uncoated Glass Beads	336.4	N/A	N/A	Low	N/A
Alumina-Coated Glass Beads	370.1	10.5	10.9	Moderate	Moderate improvement in surface morphology
Silica-Coated Glass Beads	350.2	11.2	11.7	Moderate	Slightly increased surface roughness

V. CONCLUSION

Finally, it was successful in demonstrating how heat transfer can be augmented in Fluidized Bed Reactors through the use of iron oxide coated glass beads. The surface coating resulted in very high thermal conductivity of the beads and consequently the heat transfer coefficient (HTC) of the beads was increased significantly above that of the uncoated glass beads. SEM, XRD, and BET surface area analysis characterization techniques were used to confirm the effects of the iron oxide coating to provide increased surface morphology, crystallinity and surface area which improve the thermal performance. The use of Random Forest regression model as a machine learning tool to show good accuracy in predicting the heat transfer behavior has integrated well with experimental data to yield an effective tool for predicting heat transfer coefficients (HTC). The results indicate the potential for iron oxide coatings and predictive modeling to improve industrial reactor thermal processes, and establish a base upon which thermal processes of FBRs can be designed and operated more efficiently. This approach provides an eligible procedure for heat transfer optimization in various kinds of fluidized bed systems.

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