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VANE TYPE INLET DEVICE PERFORMANCE PREDICTION BASED ON ARTIFICIAL NEURAL NETWORK

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Vane type inlet device, Schoepentoeter, Artificial neural network, Extreme Learning Machine.

Abstract

Liquid-gas separation is a critical process in industrial applications, particularly in underwater gas production facilities, where the separation of high condensate loads is essential. This study focuses on vane-type inlet devices, a key component in liquid-gas separators, which are designed to reduce gas momentum, distribute flow evenly, and prevent mist formation. A parametric study was conducted to evaluate the performance of different vane geometries using two-dimensional Computational Fluid Dynamics (CFD) simulations. A surrogate model based on Artificial Neural Networks (ANN) was developed to predict separation efficiency under varying conditions. The CFD analyses covered 150 test conditions, generated using a Latin hypercube sampling method, and included five input parameters such as contraction angle, vane spacing, and inlet velocity. The resulting database was used to train an ANN, which successfully predicted particle separation efficiency with less than 8% average error for particles sized 15-30 microns. This model demonstrates the potential for preliminary design of vane-type separators using machine learning, particularly for complex multiphase flow environments where empirical methods fall short.

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YAPAY SİNİR AĞINA DAYALI KANAT TİPİ GİRİŞ CİHAZI PERFORMANS TAHMİNİ

Anahtar Kelimeler

Kanatçık tipi giriş elemanı, Schoepentoeter, Yapay sinir ağı, Aşırı öğrenme makinesi.

Öz

Sıvı-gaz ayrımı, özellikle su altı gaz üretim tesislerinde yüksek kondensat yüklerinin ayrılmasının gerekli olduğu endüstriyel uygulamalarda kritik bir süreçtir. Bu çalışma, gazın momentumunu azaltmak, akışı eşit şekilde dağıtmak ve sis oluşumunu önlemek amacıyla tasarlanmış, sıvı-gaz ayırıcıların temel bileşenlerinden biri olan kanatçık (vane) tipi giriş elemanlarına odaklanmaktadır. Farklı kanatçık geometrilerinin performansını değerlendirmek amacıyla iki boyutlu Hesaplamalı Akışkanlar Dinamiği (CFD) simülasyonları kullanılarak parametrik bir çalışma yürütülmüştür. Değişen koşullarda ayırma verimliliğini tahmin etmek için Yapay Sinir Ağları (YSA) tabanlı bir vekil (surrogate) model geliştirilmiştir. CFD analizleri, Latin hiperküp örnekleme yöntemiyle oluşturulan 150 test koşulunu kapsamakta olup, daralma açısı, kanatçık aralığı ve giriş hızı gibi beş giriş parametresini içermektedir. Ortaya çıkan veri tabanı, 15-30 mikron boyutundaki parçacıklar için ortalama %8'in altında hata ile ayırma verimliliğini başarıyla tahmin eden bir YSA'nın eğitilmesinde kullanılmıştır. Bu model, özellikle ampirik yöntemlerin yetersiz kaldığı karmaşık çok fazlı akış ortamlarında, kanatçık tipi ayırıcıların ön tasarımı için makine öğrenimi kullanım potansiyelini göstermektedir.

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INTRODUCTION

The separation of liquid and gas phases is one of the most critical processes in industrial applications, especially in underwater gas production facilities. The design of a separator must match specific requirements such as duty, water load, and efficiency. The typical liquid-gas separators consist of several components including inlet devices, (multi) cyclones, and mist eliminators. These components are selected or combined depending on the required capacity, efficiency, and allowable pressure drop.

The inlet device is a critical component in two-phase separators, particularly in high mass flow applications. It is designed to efficiently reduce the momentum of the fluid entering the separator and generate a relatively uniform gas distribution. Common inlet devices include half-open pipe inlets and vane-type inlets which are shown in Figure 1

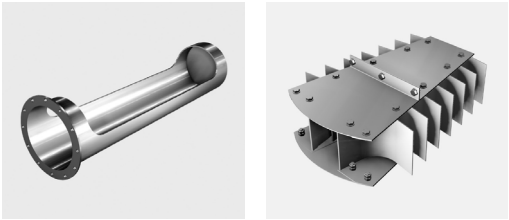


Figure 1. *Half open pipe and Vane type inlet devices* (Costacurta, n.d.).

In the industry, the selection of inlet devices is typically based on inlet momentum (ρV^2), with vane-type inlets being preferred when inlet momentum is high. (ρV^2=10000 Pa. (*Shell Global Solutions International B.V.* n.d.*). These devices are designed to effectively reduce inlet momentum by gently curving surfaces and reducing flow velocity. It is important to note that when a fluid particle hits a solid surface with high momentum, liquid can shatter into smaller droplets increasing mist load and reduce efficiency. This design also achieves far better gas distribution uniformity within the separator. However, the literature on the performance of these inlet devices is limited. One of the most comprehensive studies on this topic was conducted by Kharoua et al. (Kharoua, Khezzar & Saadawi, 2012) and later expanded by Qaroot et al. (Qaroot, Kharoua & Khezzar, 2014). Their research involved modifications to existing horizontal separators and detailed CFD (Computational Fluid Dynamics) analyses of the flow field. For instance, it is observed in this study that, when the deflector plate is replaced with the proprietary vane-type inlet device "Schoepentoeter" (developed by Shell), the results showed more uniform velocity reduction in inlet velocity and less turbulence, leading to improved particle separation. On the other hand, Qaroot et al. advanced multiphase flow analyses by considering the effects of particle coalescence and fragmentation and examined particle separation performance. These studies demonstrated that the Schoepentoeter could separate particles in the 50-100μm range with an efficiency close to 90%.*

Wehrli et al. (Wehrli et al., 2006) also conducted significant research by combining experimental and computational work on crude oil vacuum towers. They examined the performance of different inlet devices, including setups with no inlet device, a radial inlet with short vanes, and an inlet device with a Schoepentoeter. Their findings indicated that the Schoepentoeter could handle higher gas and liquid loads with better efficiency compared to other designs.

Pham et al. (Pham et al., 2018) performed similar CFD studies on vertical tanks with different inlet devices including a half-open pipe inlet and a vane type inlet device. In their first geometry, a pipe directing flow downward from two holes was used, while in the second geometry, a Schoepentoeter was employed.. Their results showed a 26.1% reduction in pressure loss and a 34.8% decrease in dead zone formation with the vane-type inlet device.

On the other hand, there are two base documents that are followed in literature for design of vane type inlet devices. The first document belongs to Shell Company (*Shell Global Solutions International B.V.*, n.d.) *whereas the second document is the manual of Petronas* (*Petronas*, n.d.). *These manuals are widely adopted for sizing and on-design performance estimation, but they do not provide capture efficiency predictions under off-design conditions. Our surrogate model complements these empirical methodologies by enabling efficiency estimation across a broader range of design parameters. Additionally, there is no established analytical method for predicting the capture efficiency of these devices, particularly due to complex flow separations and gradients. To address this gap, this study uses two-dimensional CFD simulations combined with an Artificial Neural Network (ANN) approach to create a surrogate model that predicts performance across varying conditions.*

METHODOLOGY

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics

GEOMETRY PARAMETRIZATION AND COMPUTATIONAL FLUID DYNAMICS SIMULATIONS

Geometry

The vane type inlet devices consist of repeating vanes with the same shape arranged in rows which are enclosed by plates at the top and bottom. This geometry allows for the assumption of two dimensional flow between the vanes although the flow field inside the tank is highly three dimensional. In this study, the cross-sectional geometry of the region between the vanes are parameterized and two-dimensional CFD analyses are performed. Figure 2 show the general Schoepentoeter geometry and the two-dimensional plane, respectively.

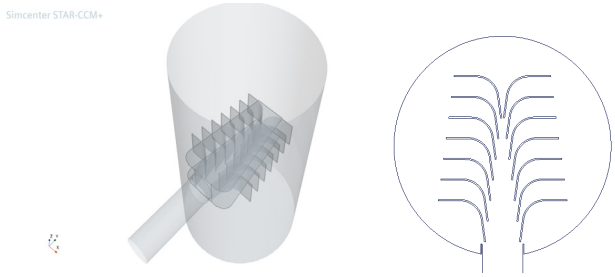


Figure 2. *3-D flow field geometry and the 2-D cutout.*

This 2-D geometry was created using the drawing program within StarCCM+ software and parameterized. Figure 3 illustrates the geometry, where the inlet and outlet flat plate

lengths were set equal, and four geometric parameters were identified: contraction angle, vertical distance between the vanes, inlet/outlet flat plate lengths, and turning radius.

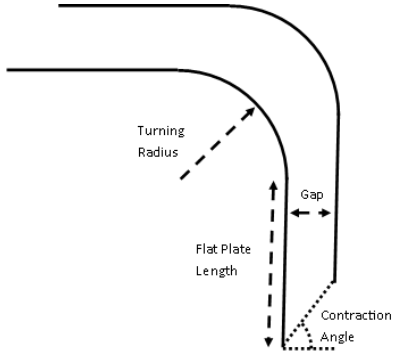


Figure 3. *Parameterized 2-D geometry.*

By including another important variable—the inlet flow velocity—the total number of input parameters becomes five.

To assess the representativeness of the 2D vane passage model, additional 3D CFD simulations were conducted on both the full separator geometry and a 3D blade passage domain. The results showed similar capture trends. For example, for 25 μm *particles, the 3D full geometry predicted ~50% capture, while the 2D model predicted ~50% capture for ~18* μm *particles for the geometry given in Figure 2. This indicates that the 2D approach slightly under predicts capture efficiency, thus providing conservative estimates. While full 3D simulations remain essential for final design validation, the 2D vane passage model is sufficiently accurate for developing surrogate models for preliminary design.*

A full factorial approach for testing all possible combinations would require an unmanageable number of simulations. Therefore, a design of experiments (DOE) approach was used, generating 150 test conditions using the Latin hypercube sampling method. During this process, uniform distribution sampling is used in equal probability regions. Parameters are treated as independent variables and no specific optimization is employed. These test conditions were then analyzed, and the results were used as input for training the artificial neural network (ANN). The ranges of the five input parameters are shown in Table 1. The test set was generated using the Python library DOEPY.

Table 1. *Input ranges*

	Minimum Value	Maximum Value	Unit
Contraction Angle	8	14	Degree
Distance Between the Vanes	0.01	0.02	m
Flat Plate Length	0.04	0.09	m
Turning Radius	0.02	0.08	m
Inlet Velocity	0	25	$m.s^{-1}$

Mesh

The StarCCM+ software allows parametric definition of the geometry, enabling automated simulation workflows. While each geometry has a unique number of grid cells, a general grid independence analysis was conducted. Figure 4 shows the variation in the capture efficiency of 15-micron particles as a function of cell count for a sample geometry. A cell count above 100,000 was deemed sufficient, and all geometries used in the study were confirmed to exceed this threshold. Beside the cell count, 20 prism layers and surface growth rate of 1.05 are used in all generated meshes.

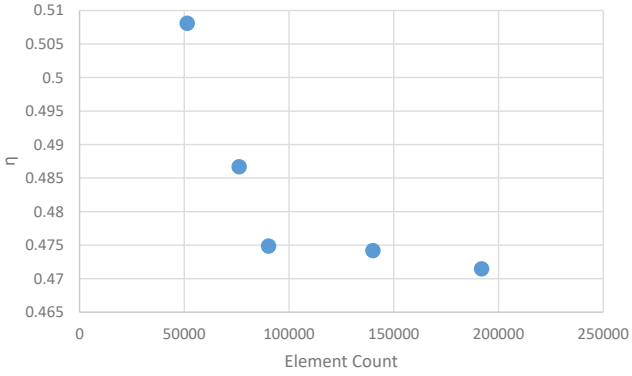


Figure 4. *Mesh independence study.*

The mesh generated for a sample geometry is shown in Figure 5.



Figure 5. *View of a sample mesh*

Computational Fluid Dynamics Formulation and Boundary Conditions

Since the flow velocities inside the Schoepentoeter are much lower than the speed of sound, incompressible flow equations are employed in the solutions. The 'Realizable k-ε' model, one of the most commonly used models in internal flows, was chosen as the turbulence model for this study. The modeling of near wall region is important in particle capturing so "two layer all y+ model" of the k-ε model is selected and a wall y+ value distribution below 1 is assured in all solutions. All simulations were performed at steady-state. The inlet turbulence intensity was set to 5% as a standard assumption for internal flows, and the outlet was modeled as a pressure outlet with zero-gradient

conditions for velocity and turbulence quantities. When the use cases of Schoepentoeter is analyzed, it is observed that the volumetric particle loading in flow field is low. One way coupling is employed in calculations where the base assumption is that the flow effects particle trajectories but particles do not change flow field. The validity of the one-way coupling assumption is supported by established fluid–particle interaction regimes, shown in Figure 6 (Elghobashi, 1994). The diagram maps coupling regimes against particle volume fraction (α_p) and the ratio of particle to fluid time scales ($\tau_p/\tau c$). In this study, the operating conditions correspond to dilute suspensions ($\alpha_p < 10^{-6}$), where one-way coupling is appropriate and particle feedback on turbulence is negligible. Even at higher velocities and for particle diameters up to 30 μm*, the particle loading remains within this regime. Due to this assumption, single-phase flow solutions are conducted and trajectories are calculated in post processing phase. Particle capture efficiency was calculated by tracking particle trajectories, with particles assumed to stick to the walls upon contact.*

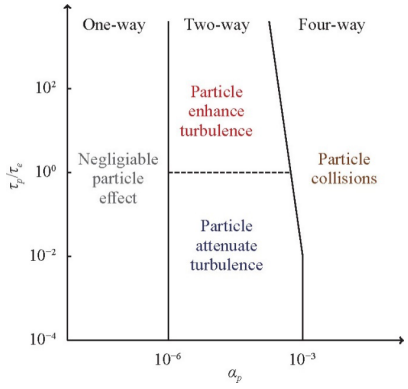


Figure 6. *Map of different regimes of interaction between particles and turbulence (Elghobashi,1994).*

The boundary conditions used for the flow simulations are illustrated in Figure 7.

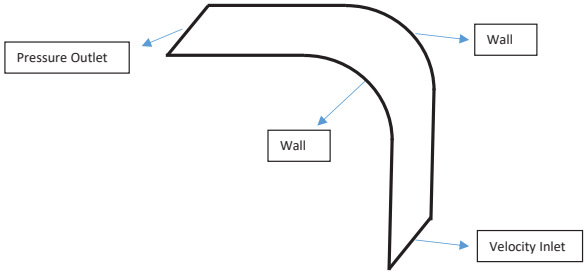


Figure 7. *Boundary conditions.*

The velocity distribution inside the flow field for two sample cases from the training set is given in Figure 8 to visualize the geometrical variation.

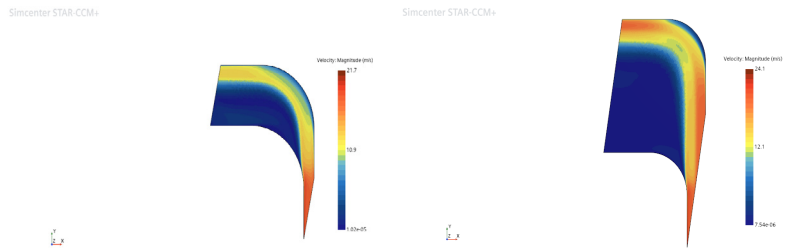


Figure 8. *Sample velocity fields calculated by CFD.*

MACHINE LEARNING

As mentioned in earlier sections, the analyses conducted to explore the possible design space have five inputs including four geometric variables and one inlet flow velocity. The outputs included particle capture efficiency for 15, 20, 25, and 30-micron particles. Given the complexity of the functional relationship between inputs and outputs, traditional statistical methods would be inefficient and inaccurate. Therefore, a machine learning approach was selected, specifically a feedforward artificial neural network (ANN) with a single hidden layer. The topology of the ANN is depicted in Figure 9.

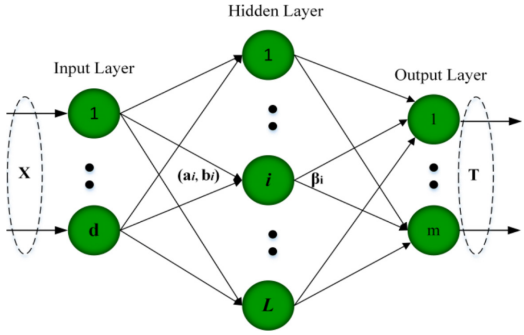


Figure 9. *Single layer feed forward neural network architecture (Jiang, Yan & Zhu, 2020).*

This simple ANN topology was chosen due to the limited size of the training set, which was constrained by the time-consuming nature of CFD simulations. Feedforward neural networks have been widely used in literature for tasks such as feature learning, clustering, classification, and regression. In this study, the ANN was employed to predict separation efficiency for conditions not included in the original training set.

Training the ANN is critical to achieving good predictive performance. Although many algorithms have been developed for this purpose, the Extreme Learning Machine (ELM) method stands out for this specific topology due to its non-iterative structure and learning speed.

In ELM, the weights of the first layer are randomly assigned and kept fixed, while the weights between the hidden and output layers are solved using linear algebra techniques. This method bypasses the potential pitfalls of gradient-based methods like backpropagation, which can get trapped in local minima. Extreme Learning Machine (ELM) was first proposed by (Guang-Bin et al., 2006) and the theoretical analysis shows that

ELM do not lose its global approximator ability with random weight assumption and more likely to reach the global optimal solution (Leung, Leung & Wong, 2019). An extensive review on ELM can be found in Wang et al. (Wang, Lu, & Wang, 2022), Huang et al. (Huang, Zhu & Siew, 2006) and Patil et al. (Patil & Sharma, 2023)

*While alternative surrogate models such as Gaussian Process Regression (GPR) or Support Vector Regression (SVR) exist, ANN with ELM training was selected in this study due to its nonlinear mapping ability, computational efficiency, and robustness with limited datasets. Literature reports (*Liu, Gao & Li., *2012) (*Mahdi, Alexandra & Nilay, *2019) confirm that ANN–ELM provides comparable accuracy to other methods for regression tasks of similar size.*

RESULTS AND DISCUSSION

A feedforward artificial neural network with 5 input layer nodes, 25 hidden layer nodes, and 1 output layer node for each particle diameter was trained using the training set generated through computational fluid dynamics. The hidden layer size was determined through manual sensitivity analysis. Neuron counts between 10 and 40 were tested, with 25 neurons yielding the lowest validation error without overfitting. On the other hand, a single hidden layer was selected to be able to employ ELM.

140 cases of 150 generated data is used for training and 10 of them are used as test cases. After the training process, the network's performance was first tested on the original training set and it was observed that the average error rate remained below 9% for all particle sizes. It is important to note that, since particle capturing ratio is nondimensional, error is directly calculated over this parameter. Considering the uncertainties within the analyses and to prevent overfitting, this error rate was deemed acceptable. The error distribution of particle capturing efficiencies is shown in Figure 10 for the training set.

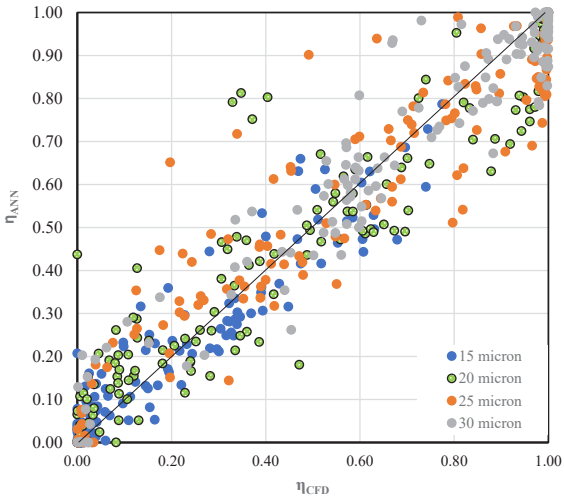


Figure 10. *Particle capturing efficiency in both CFD and ANN for training set.*

After assuring that the training set is well represented, 10 different test points which are not included in the training set were additionally analyzed as test conditions, and it was found that the average error rate in these new conditions was less than 8%. The error distribution of particle capturing efficiencies for these test cases are shown in Figure 11.

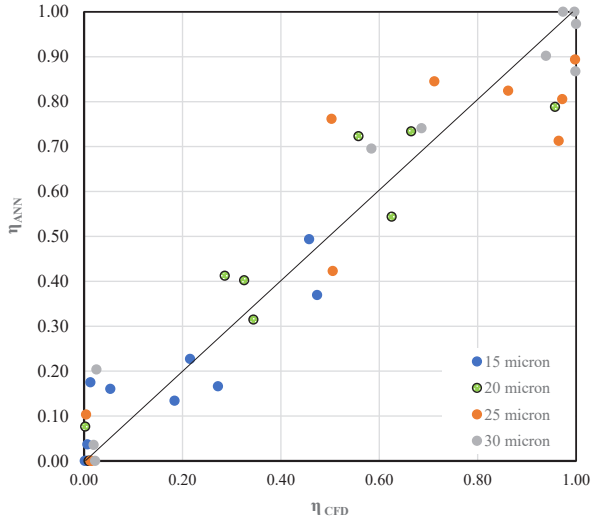


Figure 11. *Particle capturing efficiency in both CFD and ANN for test set.*

It is possible to see in Figure 10 and 11 that the error rates are similar both in training and test sets which proves the generalization capability of the developed model. Despite the outliers, average errors are in acceptable range and the variation of the average efficiency error with particle diameter for training and test sets are given in Table 2.

Table 2. *Average capturing efficiency error*

	Capturing Efficiency Average Error			
	15 micron	20 micron	25 micron	30 micron
Training Set	5.0	8.9	8.9	6.2
Test Set	6.1	8.1	11.6	6.1

Although a formal uncertainty quantification was not conducted, numerical uncertainty was partially addressed through a grid independence study and the use of Latin hypercube sampling to ensure broad coverage of the design space.

When Table 2 is analyzed, it is observed that the errors on test cases are comparable with the training set except 25 micron particles. Detailed analysis show that, for a majority of test conditions, the capturing rates have a sharp increase on 25 or 30 micron particles. Delayed or early estimation of this rise causes an error increase but the overall success is enough for preliminary design.

CONCLUSION

In this study, a surrogate model was developed to predict the performance of vane-type inlet devices using 2-D CFD simulations combined with an Artificial Neural Network (ANN) trained via the Extreme Learning Machine (ELM) algorithm. The parametric CFD study, covering 150 test conditions across five geometric and operating parameters, provided the database for model training. The resulting ANN demonstrated high predictive accuracy, with average errors below 9% for particle sizes between 15–30 μm*.*

Comparison between 2-D and 3-D simulations showed that the vane passage model yields conservative predictions of capture efficiency and is suitable for preliminary design applications where computational efficiency is crucial.

The study demonstrates that ANN–ELM is a reliable surrogate for predicting particle separation efficiency and establishes a framework that can be extended toward optimization-based separator design. From an industrial perspective, the developed approach offers a practical design aid particularly for off-design conditions where empirical correlations lack predictive capability.

Several limitations should also be acknowledged. The present work did not model coalescence and breakup phenomena, which are critical to separator performance. Incorporating these effects, together with formal uncertainty quantification and benchmarking against alternative surrogate models, will further enhance predictive accuracy.

In summary, the study demonstrates that machine learning, when coupled with CFD, can provide a fast and effective design tool for vane-type inlet devices, bridging the gap between empirical sizing manuals and full-scale multiphase CFD analyses.

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