Получение перегретого пара НРТ в теплоутилизаторе и работа его в Органическом цикле Ренкина позволит выработать дополнительную электроэнергию и повысить КПД цикла КГПУ, в который встроен теплоутилизатор с Органическим циклом Ренкина.

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DEVELOPMENT OF A COMBINED CONTROL SYSTEM OF THE ULTRAFILTRATION PROCESS FOR THE SEPARATION OF AMERICIUM AND CURIUM

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Ultrafiltration for Radionuclide Separation: An Overview

Ultrafiltration utilizes a semi-permeable membrane to separate particles. The process commonly employs crossflow filtration, where the liquid flows parallel to the membrane, minimizing fouling and allowing for continuous processing.

Ultrafiltration is cost-effective and efficient, enabling high permeate quality and waste volume reduction.

Radionuclide Separation with Ultrafiltration leverages the fact that actinide wastes often exist as colloids in radioactive waste streams. These colloids, along with suspended solids and high molecular weight organic molecules, are effectively rejected by the ultrafiltration membrane, concentrating them in the retentate stream.

Dissolved radionuclides can be pre-treated through complexing, forming larger particles that are subsequently separated by the membrane.

Neural Network Model

Neural networks are mathematical models that use learning algorithms inspired by the brain to store information. Similar to the brain, neural networks are built up of many neurons with many connections between them.

Neural networks are designed to learn from data and can be trained to perform a wide range of tasks, such as recognizing patterns, making predictions, and classifying data. They are particularly useful for tasks that are too complex or too vast for humans to perform manually and can be used in a variety of fields, including image and speech recognition, natural language processing, and predictive modeling.

By integrating a neural network model, the efficiency of the UF process is enhanced, allowing precise predictions and adaptive control.

Technological Variables of the Ultrafiltration Process

Technological variables can be described as the different factors that affect the outcome of the separation process. They can be divided into input and output variables. Input variables are the factors that can be controlled or adjusted before or during the process while output variables are the measurable results of the process.

In constructing an Artificial Neural Network (ANN) tailored for ultrafiltration processes for the separation of radionuclides, a holistic consideration of input variables is essential. Membrane properties, including pore size and surface charge, alongside operational factors such as feed flow rate, feed concentration, pH of the feed solution, temperature, feed pressure, and membrane surface area, stand out as pivotal contributors to the process's performance

Table 1. Optimization procedures for the neural network model

Optimization Strategy	Description	Potential Benefits
Data Expansion	Increase the size and diversity of the training dataset. Include data on various pollutant types, concentrations, operational conditions (temperatures, pressures), and membrane properties	Enhances model robustness, accuracy, and generalizability. Reduces the risk of overfitting
Architecture Tuning	Experiment with different: Numbers of hidden layers and neurons. Activation functions (e.g., ReLU, sigmoid)	Fine-tunes the model's complexity and learning capabilities. Improves prediction accuracy
Training Algorithm Selection	Explore alternative training algorithms (e.g., gradient descent, Levenberg-Marquardt) and adjust learning rates, momentum, and other hyperparameters	Optimizes the model's learning process. May lead to faster convergence and improved accuracy
Loss Index and Regularization	Consider different loss functions (e.g., mean absolute error, Huber loss) and regularization techniques (e.g., L1, L2) to prevent overfitting and improve generalization	Enhances model stability and predictive performance on unseen data
Incorporating Membrane Properties	Include membrane characteristics (material, pore size, hydrophobicity, etc.) as input variable.	Improves predictive power across different membrane types. Enables optimization of membrane design for radioactive wastewater treatment

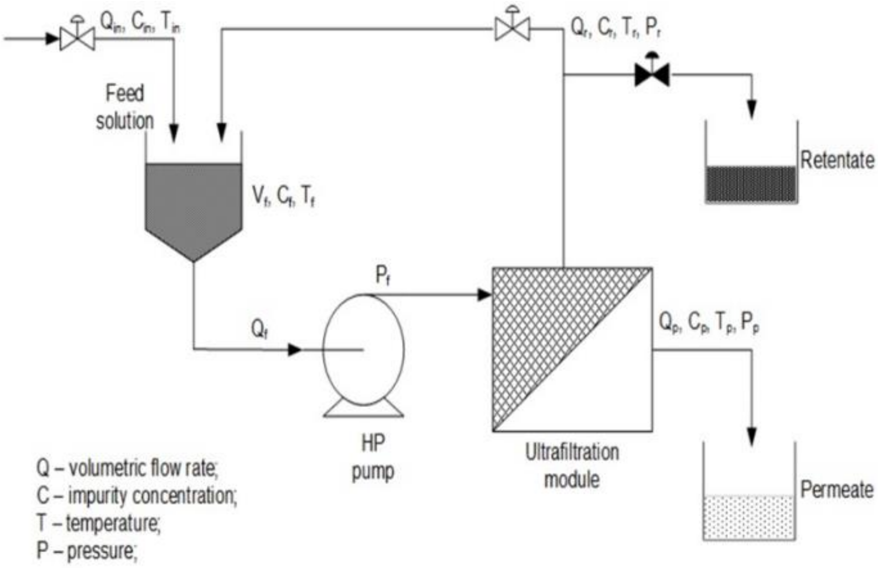

Fig. 1. Schematic diagram of the UF process

Mathematical Modeling of the Ultrafiltration Process

Conservation of mass

$$\frac{d(\rho V)}{dt} = \sum_{i:inlet} \rho_i F_i - \sum_{j:outlet} \rho_j F_j; \tag{1}$$

$$\begin{Bmatrix} \text{rate of accumulation} \\ \text{of mass in the tank} \end{Bmatrix} = \begin{Bmatrix} \text{rate of} \\ \text{mass in} \end{Bmatrix} + \begin{Bmatrix} \text{rate of} \\ \text{mass out} \end{Bmatrix}.$$

$$\frac{d(C_s V)}{dt} = Q_i C_{\text{Sin}} - QC_S;$$

$$\frac{d(CV)}{dt} = Q_{in} + Q_r - Q_f;$$

$$\frac{dC_{in}V}{dt} = C_{in}Q_{in} - C_p Q_p;$$

$$C_{in}\frac{dV}{dt} + V\frac{dC_{in}}{dt} = C_{in}Q_{in} - C_p Q_p. \tag{2}$$

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