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Surrogate assisted optimization for parameters tuning of a separator in a tapioca starch process

Sompoch Charoensuk [1)] Thana Radpukdee [1)*] and Nantiwat Pholdee [2)]

[1)] Department of Industrial Engineering, Faculty of Engineering, Khon Kaen University

[2)] Department of Mechanical Engineering Faculty of Engineering, Khon Kaen University

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Abstract

This study employs a single-objective differential evolution optimizer for surrogate-assisted optimization. A separator plant is modeled using five surrogate approaches for process optimization. The optimization objective is defined as minimizing starch loss relative to the Baume output of starch milk, while adhering to the lower and upper bounds of design parameters, including pulp input, Baume input, and regulated valve flow control. These bounds also support the plant controller's original design parameters. The optimal parameters were implemented and their real and numerical performances compared to validate the proposed method. The results demonstrate that the suitable surrogate model for the separator plant can be identified and that the optimal characteristics can be achieved, providing practical benefits to the process.

Keywords: Tapioca starch washing process: surrogate model

*ติดต่อ: rthana@kku.ac.th

1. INTRODUCTION

Air and water pollution are common consequences of processing agricultural products, particularly in the tapioca starch industry. Wastewater from tapioca starch producers, which often seeps into public canals and rivers, has become a significant contributor to Thailand's pollution problem. During large volume of wastewater treatment, carbon dioxide (CO_2) and methane (CH_4) are released, further harming the environment. Consequently, it is crucial to reduce and regulate the volume of these wastewater and harmful gases to mitigate their impact effectively.

In this instance, light starch milk spills during the process are the primary source of wastewater. One of the main points of significant leakage in the tapioca starch production process is the separator. This study aims to minimize the amount of starch released into wastewater, thereby reducing pollution caused by starch loss and improving production efficiency in the starch industry. The separator process is illustrated in Fig. 1.

In the Signal Control and Data Acquisition (SCADA) system, process data is controllable, observable, and recordable. A mass flow meter, located at position 1, measures the density of starch loss. Position 2 features a control panel for setting parameters, including starch milk input flow rate and output starch density. At position 3, a proportional valve is installed, equipped with an adaptive PID flow controller. This controller adjusts its gain dynamically in response to changes in the setting input parameters and the target output density.

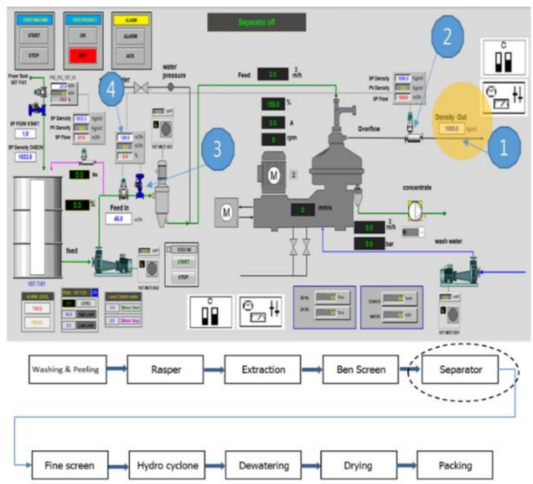

Figure 1 A separator SCADA and the tapioca starch production process

The separation mechanism is highly intricate, making the cost of direct mathematical modeling prohibitively high. To address this, the surrogate technique is employed to assist in the optimization process, enabling the determination of ideal design parameters to reduce starch loss and increase starch density output. This technique is commonly used in research to enhance industrial production efficiency.

Jin, W. et al. (2022) [10], while optimizing a high-temperature reservoir thermal energy storage (HT-RTES) system, developed a machine learning model comprising a Bayesian search algorithm and two deep-layer artificial neural network (ANN) models. This approach, which accounted for operational scenarios and site-specific variables, produced more reliable and efficient energy storage solutions.

Chen, X. et al. (2021) [4] enhanced the operational performance of fluidized catalytic crackers in real-time refinery applications. By estimating the load in real time and reducing the order of the cracker model, they improved the trust region filter optimization process.

Franzoi, R. E. et al. (2021) [5] integrated sequential linear programming techniques, trust region methods, and adaptive sampling strategies into an optimizer to reduce lag time and convergence issues. The performance of the adaptive sampling iteration was evaluated using a surrogate model of the response system.

Surrogate models are particularly vital for modeling extremely nonlinear plants or machines that are prohibitively expensive to simulate. For example, Ali, W. et al. (2018) [2] employed an RBF-thin plate spline to model the mixed refrigerant liquefaction process. Additionally, surrogate models can be applied to adaptive controller tuning of brushless direct current motors for speed regulation using the response surface approach (Rojas-López, A. G. et al., 2024 [7]).

In numerical simulations for plant modeling, high-order spatio-temporal discretization is often necessary for highly nonlinear models, such as those employed in complex thermo-mechanical structure analysis using the finite element method (FEM), material characterization, tribological contact, significant deformation, or damage scenarios. Bagheri, S. et al. (2021) [3] used RBF meta-modeling for these nonlinear FEM problems, avoiding the need for direct FEM calculations.

In our work, we utilized five popular surrogate models to simulate a real-world plant, aiming to optimize the reference parameters of the PLC controller. A summary of the five surrogate modeling techniques is presented in Section 2. Sections 3 and 4 focus on the problem formulation and the numerical setup. Section 5 provides a comparison of the optimization results and surrogate modeling outcomes for each method. Finally, the conclusions are outlined in Section 6.

2. SURROGATE MODELLING

A separator machine is employed in the starch washing process to enhance starch concentration and purify starch milk. This phase of the operation is referred to as the concentration stage (see Fig. 3). A nozzle, which uses counter wash water for starch purification, is fed with heavy starch particles that were casted via centrifugal force generated by a series of discs attached to a shaft. Once cleaned, the starch particles are collected and discharged through an outlet pipe. However, the wash water feed pressure can lead to contamination and cause some starch particles to overflow from the top of the separator.

While computationally expensive Computational Fluid Dynamics (CFD) modeling can be used to simulate the combined gravity-centrifugal and washing phenomena, real-time testing remains impractical. This is true even under conditions where the machine rotates at a constant speed with a fixed wash water flow rate. Surrogate modeling offers a more efficient alternative to state-space or other system identification techniques, as it significantly reduces the computational effort required during the optimization process.

As noted by Wahid Ali et al. (2018) [2], surrogate models transform complex processes into reduced-order models, making them an attractive choice. This study explored a suitable model capable of representing the intricate dynamics of the starch washing process. The following modeling techniques were applied, with much of the detailed methodology and algorithms drawn from the work of Alexander I. J. Forrester, András Sóbester, and Andy J. Keane (2008) [1]. The following is a synopsis of each technique.

2.1. Through RSM modelling

Given $[X] = [\boldsymbol{x}_1, \dots, \boldsymbol{x}_n]^{\mathrm{T}}$ is a matrix of desig n vector for *n* sampling points and $[F] = [\mathrm{f}_1, \dots, f_n]^T$ represents a function value correspo nding to X. The polynomial response surface mo del (RSM) used to estimate $\hat{f}$ can be expressed as follows:

$$\hat{f}(\boldsymbol{x}) = \mathbf{x}\boldsymbol{\beta} + \boldsymbol{c} \tag{1}$$

Where $\boldsymbol{x}$ is all the polynomial terms of vector of design variable, $\boldsymbol{\beta}$ is the vector of regression coefficients.

The $\boldsymbol{\beta}$ and $\boldsymbol{c}$ can be found as follows;

$$\boldsymbol{\beta} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{F} \tag{2}$$

$$\boldsymbol{c} = \boldsymbol{F} - \boldsymbol{X}\boldsymbol{\beta} \tag{3}$$

Where $\boldsymbol{X}$ is all the polynomial terms of all sampling points.

2.2. Through RBF modelling

The RBF (radial basis function) samples a set of $[X]$ with its function $[F]$. The radial basis function model (RBF) is used to estimate $\hat{f}$ can be expressed as follows

$$\hat{f}(x) = \sum_{i=1}^{n} C_i K(\|x - x_i\|) \tag{4}$$

Where K is kernel function. C_i is an interpolant coefficient to be found. By setting the interpolation function $\hat{f}(x_i) = f_j$, Defining the Euclidean distance term $\|x_j - x_i\| = r_{ji}$, the coefficient can be determined. And a matrix form of the RBF construction is

$$[K(\|x_j - x_i\|)]\{C_j\} = \{f_j\} \quad (5)$$

and C_i can be found as

$$\{C_j\} = [K(\|x_j - x_i\|)]^{-1}\{f_j\} \quad (6)$$

The radial basis r_{ji}, can be selected from various types, such as Linear spline, Cubic spline, Thin plate spline, Gaussian, Multiquadric, Inverse quadric, Inverse multiquadric, Bump function, or others. It is important to note that the radial basis function matrix is symmetric. To ensure that Equation 6 has a unique solution, the chosen basis function must be non-singular.

2.3. Through KRG modelling

The Kriging (KRG) surrogate model is constructed using a Gaussian correlation function and a polynomial trend model, as outlined by M. Kumar et al. [18]. The KRG prediction function is defined as:

$$\hat{f}(\boldsymbol{x}) = p(\boldsymbol{x})^T\boldsymbol{\beta} + \boldsymbol{\psi}^T\boldsymbol{\Psi}^{-1}(\boldsymbol{F} - \boldsymbol{p\beta}) \quad (7)$$

where

$\boldsymbol{\beta}$ represents the regression coefficients,

$\boldsymbol{\psi}$ is the correlation vector between

$\boldsymbol{x}$ and each sample point,

$\boldsymbol{\Psi}$ is the correlation matrix between sample points.

The KRG correlation function is given by:

$$\psi(\boldsymbol{x}_i, \boldsymbol{x}_j) = exp(-(\boldsymbol{x}_i - \boldsymbol{x}_j)^T\boldsymbol{\theta}(\boldsymbol{x}_i - \boldsymbol{x}_j) \quad (8)$$

where $\boldsymbol{\theta} = \{\theta_1, \theta_2, \ldots, \theta_k\}^T$ are the correlation parameters, estimated by maximum likelihood. In this study, the MATLAB DACE toolbox is used fo r constructing the Kriging model.

2.4. Through SVR modelling

Support Vector Regression (SVR) is a variant of Support Vector Machine (SVM) that excels in regression tasks due to its strong learning capabilities. In SVR, the term "support vectors" (SV) refers to the data points closest to the regression model's decision boundary, which defines the maximum margin. By utilizing an optimal decision-making surface, SVR effectively separates data points within a specified margin, thereby balancing model complexity and prediction accuracy. This maximum-margin approach also mitigates the risk of overfitting by ensuring that the model generalizes well to unseen data (Hu A et al., 2023 [6]).

In simple terms, as described by Alexander I. J. Forrester et al. (2008) [1], the SVR predictor function can be expressed as:

$$\hat{f}(\boldsymbol{x}) = \boldsymbol{w}^T\phi(\boldsymbol{x}) + b \quad (9)$$

Where

w is weighting factor,

$\boldsymbol{\phi(x)}$ is mapping function that transforms input x into a higher-dimensional feature space,

b is bias term.

The weight vector ***w*** is found by solving the following optimization problem

$$\min: \frac{1}{2}|\boldsymbol{w}|^2 + C\sum_{i=1}^{n}(\xi_i - \xi_i^*) \quad (10)$$

Subject to:

$$f_i - \hat{f}(\boldsymbol{x}) \le \varepsilon + \xi_i$$

$$\hat{f}(\boldsymbol{x}) - f_i \le \varepsilon + \xi_i^*$$

where

ξ_i and ξ_i^* are slack variables for data points outside the margin

C is regularization parameter controlling trade-off between margin width and prediction error.

2.5. Through NNB modelling

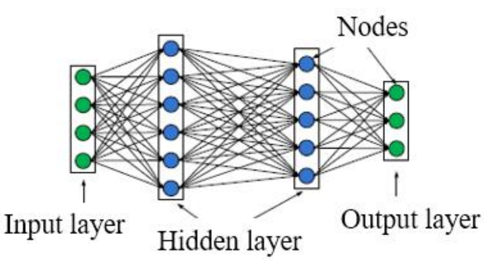

Figure 2 A feed-forward 4-6-5-3 network.

Neural network (NN) modeling comprises interconnected nodes that mimic the behavior of neurons in living organisms. A feed-forward multilayer network typically includes input, hidden, and output layers, as illustrated in Figure 2.

The NN estimation function at the output layer is represented as:

$$\hat{f}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{Z}\boldsymbol{w}^{(2)} + \boldsymbol{b}^{(2)}) \quad (11)$$

where the hidden layer output ***Z*** is defined as:

$$\boldsymbol{Z} = \boldsymbol{g}(\boldsymbol{x}\boldsymbol{w}^{(1)} + \boldsymbol{b}^{(1)}) \quad (12)$$

where

$\mathbf{w}^{(1)}$ and $\boldsymbol{w}^{(2)}$ are the weight matrices from the input layer to the hidden layer and from the hidden layer to the output layer, respectively,

$\boldsymbol{b}^{(1)}$ and $\boldsymbol{b}^{(2)}$ are bias vectors for the hidden and output layers, respectively,

g and ***f*** are the activation functions for the hidd en and output layers.

The weights w and biases b in a neural network are optimized through a training process, commonly using backpropagation in conjunction with an optimization algorithm such as gradient descent. During training, the network iteratively adjusts these weights to minimize a cost function, which quantifies the difference between predicted and actual outputs. This adjustment allows the network to learn patterns from the training data and generalize effectively to unseen testing data.

3. PROBLEM FORMULATION

Between the bent screen, which filters starch milk from the extractor, and the fine screen, which further refines the milk before it is sent to the hydro cyclone for purification, lies the separator process used in tapioca starch production (see Fig. 1). As shown in Fig. 3, the primary cause of starch loss during this separator step is the washing process.

At the top of the separator, a feed pump and a proportional flow control valve feed and regulate the starch milk coming from the extractor. Washing water is introduced from below. The dense starch milk is then cleaned, centrifuged, and discharged as concentrated starch milk, which proceeds to the hydro cyclone process. Meanwhile, the light phase discharge is expelled as wastewater, and the medium phase waste is returned to previous washing stages.

According to the company's SCADA system, the annual starch loss attributed to this light phase discharge is approximately 1,000 tons, equivalent to a financial loss of 14 million baht annually. The factory has a production capacity of 220,000 tons of starch per year and consumes around 1,000,000 tons of raw tapioca annually.

To enhance this process, a proportional flow control valve can be employed to regulate the starch milk intake, thereby reducing significant losses. The valve's opening is adjusted based on preset parameters and feedback signals from a starch density meter positioned in the wastewater drain section. The relationship between specific gravity and starch density data from the case study plant is used to calculate starch loss in the drain wastewater.

To develop a surrogate model for determining the optimal input flow settings, the following design variables were considered:

1. **Pulp Input** (% ml Pulp/ml Starch Milk)
2. **Baume Input** (˚Be input) of the starch milk feeding into the separator
3. **Flow Rate Allowance** (Q in m^3/hr.) from the valve regulator

The plant's SCADA system can be utilized to collect and monitor these design variables, enabling accurate modeling and optimization of the process. Note that the pulp input and Baume input are collected each hour from two buffer tanks before and after the separator process by a worker then fill their wet lab data into the SCADA.

The objective function is designed to simultaneously:

1. **Maximize** the concentration of starch (˚Be output) in the discharged starch milk.
2. **Minimize** the starch loss (Ls in grams per liter) in the wastewater, as measured by an additional density meter installed on the wastewater line.

This dual objective ensures an optimized balance between product recovery and waste reduction in the starch production process.

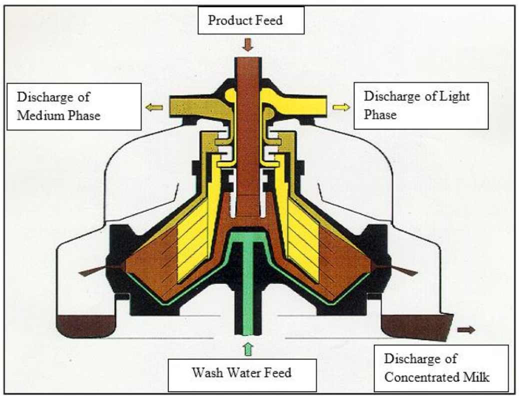

Figure 3 The crossection schematic diagram of a separator

Thus, the objective function can be expressed as follows:

Min: $f(X)\frac{Ls}{°Be\ output}$ (13)

Subject to:

$0 \le Pulp\ input \le 3$

$3 \le °Be\ input \le 8$

$130 \le Qin \le 200$

Where

$X = [Pulp\ input, °Be\ input, Qin]^T$ is a vector of the design variables with constrains.

4. SURROGATE-ASSISTED OPTMIZATION AND NUMERICAL EXPERIMENT SET UP

Surrogate modeling is essential for understanding the system's behavior, especially given the complex mechanisms involved in the washing process of derived starch milk. Despite the intricate dynamics, the optimization process is simplified by its single objective function and the limited number of design factors.

In this study, the optimizer used was the Single Objective Differential Evolution (SODE). Surrogate models, developed using PRS, RBF, KRG, SVR, and NNB approaches, were employed to approximate the behavior of the nonlinear complex plant, reducing computational effort. Further research is necessary to evaluate which surrogate model provides the most accurate tracking of the training dataset and yields suitable design parameters for the PLC controller.

SODE, as described by Sujin B. (2013) [9], optimizes by iteratively evolving the population vector of design parameters through differentiation, mutation, and selection, ultimately deriving an optimal solution. This approach effectively balances exploration and exploitation in the optimization process.

The SODE procedure is shown below.

SODE algorithm:

<u>Beginning process</u>

Define all design parameters and their initial population with respect to their objective function.

<u>Calculation process</u>

1. If a cost function has met, stop seeking solutions. If the cost function hasn't met go to the

2nd step.

2. Generate population of the design parameters by using mutation and crossover methods.

3. Calculate the objective function of the offspring from the 2nd step.

4. choose population for the next iteration from the prior parent and offspring population.

5. Interchange population position randomly then go to the 1st step.

The operators of the Single Objective Differential Evolution (SODE) algorithm fall into three primary categories:

1. **Crossover**: Combines parent solutions with mutated solutions to create offspring, promoting diversity in the population.

2. **Mutation**: Generates new candidate solutions by perturbing existing ones, enabling exploration of the search space.

3. **Selection**: Chooses the best solutions from the current population and offspring for the next generation, ensuring convergence toward the optimal solution.

The processes of mutation and crossover are mathematically described by the following equations:

$$\boldsymbol{u_i = X_{i1} + F(X_{i2} - X_{i3})} \tag{14}$$

Where

$F \in [0,1]$ is a scaling factor.

u_i is a mutation solution vector.

X_{i1} is the best so far solution vector.

X_{i2} and X_{i3} are random solution vectors in the member of a current population and $X_{i2} \neq X_{i3}$.

$$\boldsymbol{v_{i,j} = \begin{cases} u_{i,j}; rand \leq CR \\ x_{i,j}; rand > CR \end{cases}} \tag{15}$$

where $CR \in [0,1]$ is a crossover rate and *rand* is a uniform random number in [0, 1].

Index *i* refers to the ith solution in the current population, while index *j* represents the *j*th element in a solution vector.

In the fourth step of the selection procedure, the design parameters of the parent and offspring solutions (X_i) are compared simultaneously. The next population for the subsequent iteration is selected based on the solutions that provide the best performance according to the objective function. This ensures that the algorithm retains the most optimal solutions while continuing to evolve.

For this study, the following parameters were used in the SODE optimization process:

- Crossover Rate (CR): 0.8
- Scaling Factor (F): 0.5
- Probability of Selecting an Element from the Offspring: 0.7

These parameter settings guided the evolution of the population while balancing exploration and exploitation.

For the numerical experiment, the surrogate models served as representations of the plant. Below is an illustration of the technique used to develop the plant's meta-model, highlighting the integration of surrogate modeling and optimization to identify the optimal design parameters.

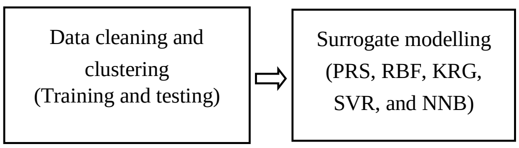

Figure 4 Surrogate modelling procedure

The SCADA system samples data from the separator process every hour, providing continuous monitoring and recording of operational parameters. The separator operates non-stop throughout the day, ensuring a consistent flow of data for analysis and optimization. As stated earlier, the pulp and Baume parameters were sampled manually each hour from buffer tanks at the product infeed line and the discharge starch milk line. These samples were analyzed in a wet lab, and the results were subsequently fed into the SCADA database, while the flow rate was continuously logged by an inline sensor. However, the manual sampling and wet lab analysis may introduce errors, particularly if the sampling interval is reduced to less than one hour, as human limitations could affect consistency and accuracy.

To mitigate the risk of over-prediction in the surrogate model, a data-cleaning process is performed. Specifically, **K-means clustering** is employed to eliminate redundant or overly similar data points, ensuring a more representative and well-distributed dataset for model training and testing. This step enhances the robustness and accuracy of the surrogate model.

After the data cleaning process, 80% of the dataset was allocated for training, while the remaining 20% was reserved for testing on unobserved data. K-means clustering was utilized to group the training data and ensure a well-distributed dataset, avoiding any clustering bias. The training dataset was then prepared and fed into the modeling algorithms: PRS, RBF, KRG, SVR, and NNB. Each algorithm was configured as follows:

- PRS (Polynomial Response Surface): Used a second-order polynomial function to approximate the system's behavior.
- RBF (Radial Basis Function): Employed a Gaussian kernel as its basis function to model complex non-linear relationships.
- KRG (Kriging): Utilized a linear model with a Gaussian correlation function to capture the global and local trends of the data.

- SVR (Support Vector Regression): Applied a radial basis function (RBF) kernel to predict the response surface accurately.
- NNB (Neural Network Backpropagation): Also utilized an RBF kernel for its activation functions to model non-linear relationships effectively.

Ultimately, these five surrogate models were constructed to facilitate the optimization procedure, leveraging their individual strengths to approximate the behavior of the separator process and identify optimal design parameters.

5. RESULTS AND DISCUSSION

The SCADA system, as previously mentioned, collected raw data over a period of 31 days, sampling at a rate of one data point per hour, 24 hours a day. K-means clustering (Alexander I. J. Forrester et al., 2008 [1]) was applied to clean the dataset by consolidating repeated value parameters into a single entry. This resulted in a refined dataset shared across all design fields. The dataset was then randomly divided into training (80%) and testing (20%) groups, ensuring that the testing domain was adequately covered by the training domain (as illustrated in Figures 5–8).

Due to a hydro-cyclone process constraint near the separator, the target Baume output (˚Be output) was set to approximately 18–19 ˚Be, with the goal of minimizing starch loss (Ls). Adjustments to the flow rate through the regulated valve revealed an inverse relationship: a lower Baume input resulted in a higher flow rate, and vice versa. An adaptive precision PID controller (outside the scope of this study) regulated this adjustment to reduce starch loss in wastewater.

Although Figures 6 indicates the potential for nearly zero loss at Baume inputs between 3 and 4 ˚Be, this range is not recommended due to the low efficiency of prior starch extraction methods. Additionally, data suggests that at Baume inputs above 4 ˚Be, there is a substantial concentration of nearly zero-loss conditions. Consequently, Baume inputs in the range of 4.5 to 8 ˚Be were considered. However, inappropriate control of the valve's flow rate could lead to increased losses at higher Baume inputs. Figures 5 and 7 also show that flow inputs of approximately 100 to 200 m^3/hr. yield high Baume outputs (density of the high ˚Be output point cloud along that range), though it remains unclear if higher pulp inputs lead to greater losses.

To address these relationships, surrogate models were employed to investigate and optimize the process. The meta-modeling approach was used to mitigate initial losses caused by incorrect or transient control parameter settings and to estimate initial setpoints (X_i) for the PLC controller, avoiding fluctuations due to the plant's nonlinear behavior.

The cleaned dataset (80% for training and 20% for testing) was then utilized to construct surrogate models, including PRS, RBF, KRG, SVR, and NNB. The performance of each model was evaluated using the Root Mean Square Error (RMSE), which quantified the accuracy of the objective function estimations. These results informed the selection of the most effective surrogate model for optimizing the separator process.

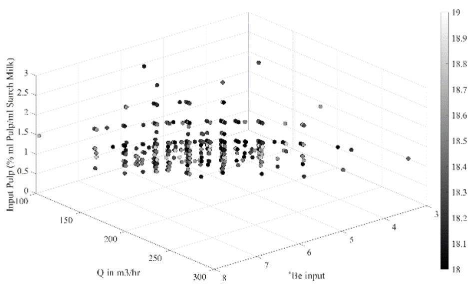

Figure 5 The training °Be output cleaned data VS its variables

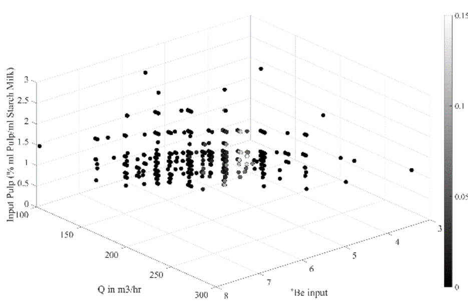

Figure 6 The training Ls cleaned data VS its variables

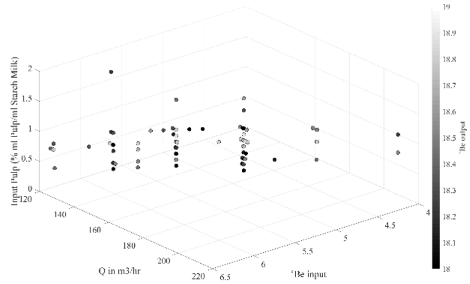

Figure 7 The testing °Be output cleaned data VS its variables

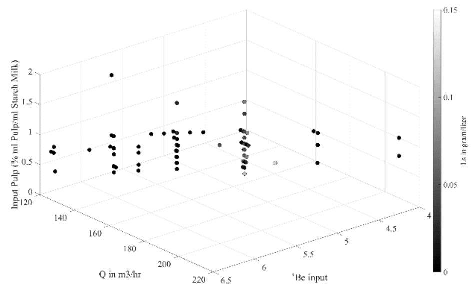

Figure 8 The testing Ls cleaned data VS its variables

The Root Mean Square Error (RMSE) for each surrogate model is displayed in Figure 9. It was observed that the Radial Basis Function (RBF) model exhibited the lowest error in plant estimation, with the Support Vector Regression (SVR) model also achieving comparably low errors. This highlights the strong performance of both models in accurately approximating the plant's behavior.

Although the rankings of the surrogate models were determined (with RBF and SVR ranking first and second, respectively), the final determination of the optimal design variables for each model

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requires the application of the Single Objective Differential Evolution (SODE) optimizer. This step ensures that the surrogate models provide the most effective solutions for the separator process optimization, aligning model estimations with real-world performance requirements. The **PLC's supervisory input** was subsequently configured using the optimal design parameters derived from the surrogate models. This ensured that the process control system operated at its most efficient settings, effectively aligning the plant's performance with the optimization objectives.

Table 1 presents the results for the optimal design variables, the estimated objective function values, and the actual objective function values based on the optimal parameters. Among the surrogate models:

- SVR and RBF provided the most accurate estimations, with comparatively low discrepancies between the modeled and actual objective function values.
- KRG produced the highest Baume output (°Be output) according to the actual plant data, showcasing its potential for maximizing starch concentration.
- SVR, ranked second, demonstrated a strong balance between minimizing starch loss and achieving high Baume output, making it a reliable option for practical application.

These findings highlight the strengths of each model and their respective suitability for different aspects of the optimization process.

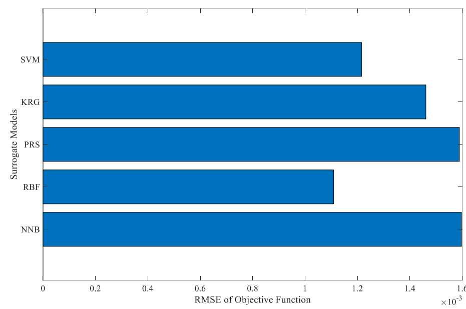

Figure 9 The RMSE of each surrogate model.

In practice, the plant's target Baume value (°Be) typically ranges between 18 and 20. Interestingly, the Kriging (KRG) model yielded an unexpected objective function result of -1. Despite this anomaly, when comparing objective function values across surrogate models, the KRG model ultimately provided the most accurate true optimal solution. This outcome highlights the 'blessing and curse of uncertainty' often encountered in surrogate-assisted optimization [8], [11]. Although the KRG model had high RMSE among the surrogate models, it demonstrated the ability to best capture the true function profile of the system. Conversely, the Support Vector Regression (SVR) model achieved the lower RMSE, indicating superior accuracy in estimating plant behavior. The SVR model also produced °Be values and starch loss metrics closely aligned with those of the KRG model (see Table 1), making it a robust choice for practical applications where precise estimation is critical.

The authors recommend Support Vector Regression (SVR) as the most suitable meta-model overall, given its superior performance in profile tracking and accuracy. Compared to other models:

- The Polynomial Response Surface (PRS) model had a low input flow setpoint that rendered it unsuitable for proper separator operation.
- The Radial Basis Function (RBF) and Neural Network Backpropagation (NNB) models produced ideal ˚Be inputs that were too small for practical application.
- The numerical calculations in some models yielded negative signs in the objective functions, which can be interpreted as a scenario where the objective function comparison error is effectively zero. However, high RMSE values and impractical flow control settings made PRS and NNB unsuitable.
- Additionally, the low flow rates suggested by these models could prolong the washing process, further reducing operational efficiency.

This work aimed to identify the best design parameters and a surrogate method capable of accurately mimicking the separator's behavior. The SVR model demonstrated minimal objective function errors (as shown in the final column of Table 1) and provided ˚Be inputs within a practical range of 3–8 ˚Be. Values close to the bounds were avoided, as they were deemed impractical for real-world use.

In comparison to the Kriging (KRG) model, the SVR offered more consistent results with minimal errors and was ultimately chosen as the optimal surrogate method for this study.

By utilizing the SCADA reference values as the optimal settings for the proportional valve controller, the annual light-phase starch waste of approximately 1,000 tons was effectively eliminated. This recovery allowed the starch to be returned to the production process, yielding a financial benefit exceeding 14 million baht per year.

Reducing the discharge of light-phase starch into wastewater not only minimizes waste but also significantly lowers the chemical oxygen demand (COD), which directly impacts the need for extensive wastewater treatment. Additionally, this reduction curtails the production of greenhouse gases such as carbon dioxide (CO_2) and methane (CH_4), which are typically generated during the treatment process. The decrease in wastewater also reduces energy consumption associated with treatment, further contributing to environmental sustainability and the reduction of greenhouse gas emissions.

Table 1

A comparison of the estimated objective function and the real one with respect to the optimal design variables.

Surrogate models	Design variables			Objective functions		f opt	Objective functions Real		f Real
	Pulp (% ml Pulp/ml Starch Milk)	°Be input	Flow control (m^3/hr)	°Be output	loss in g/l		°Be output	loss in g/l	
PRS	3	6.0591	130.0000	17.8988	-0.0269	-0.0015	18.8000	0.2527	0.0134
RBF	3	3.9977	157.0740	18.1928	-0.0119	-0.0007	17.6000	0.1159	0.0066
KRG	2.681	4.8835	176.4254	-3.1029	3.1029	-1.0000	19.0000	0.0180	0.0009
SVR	2.9543	4.7955	173.5075	18.3356	-0.1046	-0.0057	18.8000	0.0328	0.0017
NNB	1.1651	3.3598	151.5323	17.5914	-0.0760	-0.0043	17.3000	0.1413	0.0082

6. CONCLUSIONS

The supervisory parameters of the starch milk separator plant were successfully optimized using surrogate-assisted techniques. Five well-established surrogate models were developed based on SCADA data, with the pulp input, °Be input, and regulated valve flow control selected as the design parameters. The best possible solutions for these parameters were then identified. Using the objective function, which considered starch loss (Ls) and Baume output (°Be output), the Single Objective Differential Evolution (SODE) optimizer was employed. The initial parameters of the separator plant were established based on the optimization results while accounting for the plant's capabilities and operational constraints.

The comparative analysis demonstrated that the Support Vector Regression (SVR) model provided the best overall performance in modeling and optimizing the separation process. The SVR model not only accurately estimated the separator's functional profile but also delivered an optimal solution that, under real operating conditions, achieved superior results in terms of output and minimized loss.

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