Multi-objective optimization of batch electrodialysis for minimizing energy consumption by using non-dominated sorting genetic algorithm (NSGA-II)

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Abstract. From the solid waste of palm oil, i.e. empty fruit bunch (EFB), sugar can be produced through the hydrolysis process by using hydrochloric acid (HCl). The acid must be separated from the sugar to produce pure sugar and to reduce the processing costs by recovering and recycling the hydrochloric acid. Electrodialysis (ED) which is a membrane separation characterized by an electrical field orthogonal to the membrane, is a feasible method for acid recovery. In the ED process, there are conflicting objective functions, i.e. maximum concentrated and minimum energy consumption which cannot be solved by single objective optimization technique. Simultaneous optimization of these objectives yield in a multi-objective optimization (MOO) problem, which is characterized by a set of multiple solutions, known as pareto solutions. In this work, a non-dominated sorting genetic algorithm (NSGA-II) approach was used to generate the pareto solutions for two objectives: maximize concentrated acid and minimize energy consumption, for the batch ED. Each point of Pareto solutions consists of different optimal current density and flowrate profiles, which lead to distinct amount of energy consumption and acid concentration. These solutions give flexibility in evaluating the trade-offs and selecting the most suitable operating policy.

1. Introduction
Approximately 90% (by weight) the oil palm tree which includes oil palm fronds, fresh fruit bunch, and oil palm trunk was remnant as oil palm wastes. The percentage of fresh fruit bunch of oil palm which is retrieved as palm oil is only 21.6% (by weight), residual as biomass and that includes the palm kernel and solid wastes which comprise of empty fruit bunch (EFB), mesocarp fibre and shell. From the EFB, sugar (glucose) can be generated via the hydrolysis process by using hydrochloric acid (HCl) [1].

Electrodialysis (ED) found to be a feasible technique because it could concentrate the hydrochloric acid for recovery and could save consumption of the alkali for the neutralization process. In the ED process, the main factor of separation is ionic transport where an electric field exists in the electrolyte solution. The electrochemical system which occurs, such as potential drop and resistances, will affect the separation process and energy consumption significantly. Current density is the driving force of ED. Increasing current obviously enhances the ion transport through the membranes. However, energy
consumption should be taken into consideration along with concentration efficiencies. Therefore, there must be an equilibration attached between energy consumption and concentrated acid. Proper optimization can significantly improve the ED performances as make the high acid concentrated with less energy consumption [2].

The available literature on the optimal operation of the ED process for acid-sugar separation focuses on solving single objective optimization problems by considering decision variables as constant or varying with time [3]. However, in the ED process, there are conflicting objective functions, i.e. maximum concentration in concentrated compartment and minimum energy consumption which leads to significantly different optimal operating conditions. The solution of the single-objective optimization problem does not produce such useful information about the relationship among the several objective criteria, and a set of decision variables so readily. It will not be possible to find a unique solution which is simultaneously optimal for all the objectives. Thus, it can be expected that use of a multi-objective optimization MOO approach for the developing optimal policy can provide a better handle for predicting performance trade-offs arising due to conflicting operating objectives for the ED process [4]. Despite this, application of multi-objective optimization to the ED for acid-sugar separation process has been unexplored. The investigation of MOO in the ED process can fill the gap for ED batch optimization study.

The objective of this paper is to solve the multi-objective optimization problem in batch electrodialysis for acid recovery. The aim of this optimization problem is to determine the optimal current density and flowrate profiles to optimize the objective functions which are minimization energy consumption and maximization acid concentration in concentrate tank.

2. Process modelling of batch Electrodialysis

In this work the irreversible thermodynamic (IT) approach is implemented. The IT represents simple mathematical tool for linking the flux of species through the membrane with the interfacial concentrations of this species at the left-hand and the right-hand sides, as well as with the external driving forces, the electric current in the case of the ED.

The assumptions made in developing the ED model are; boundary layers adjacent to the membranes in which the solutions are completely static; the solution in the interior of a solution compartment (i.e., between the boundary layer) is thoroughly mixed so that the concentration of the electrolyte at any point in this zone is the same as at any other point; there is no change of either the thickness of the boundary layer or the gradient along the flow channel; the flow dynamic conditions are similar in all compartments; the distribution of pressure and current is uniform; trans-membrane pressure is zero; no solution leakage in the membrane and during the operation the current density is not exceeded the limiting current density [5].

The schematic of ED with batch recirculation unit is presented in Figure 1. The component material balances in concentrate and dilute compartments are:

\[
\frac{d(C_{\text{conc}})}{dt} = \frac{Q(C_{\text{conc}}^T - C_{\text{conc}}) + \left(\frac{t_a}{F} - D(C_{\text{conc}} - C_{\text{dil}})^jF}{jF} - D_a(C_{\text{Bf,c}} - C_{\text{Bf,d}})l_a\right)NA_m}{NV_{\text{comp}}} + \frac{-D(C_{\text{Bf,c}} - C_{\text{Bf,d}})}{l_a}NA_m - C_{\text{conc}}^T \left(\frac{t_w}{F} + L_w(C_{\text{conc}}^T - C_{\text{dil}})\right)NA_mV_w}{NV_{\text{comp}}} \quad (1)
\]
Consumption in ED Process is calculated with the following expression:

$$ Q(C_{\text{conc}}^T - C_{\text{dil}}^T) = \left( \frac{(t_e + t_0 - 1) - D(C_{\text{conc}} - C_{\text{dil}})^F}{F} \right) - \frac{D_a(C_{Bf,D} - C_{Bf,C})}{l_a} \frac{F}{W} $n$$

$$ \frac{d(C_{\text{dil}})}{dt} = \frac{1 - D_c(C_{Bf,C} - C_{Bf,D})}{l_e} \frac{F}{W} \frac{NA_m}{V_{\text{comp}}} $$

$$ \frac{d(C_{\text{conc}})}{dt} = \frac{Q(C_{\text{conc}} - C_{\text{dil}})}{V_{\text{conc}}} \left( T \frac{F}{W} \frac{t_e}{J} + (L_W(C_{\text{conc}}^T - C_{\text{dil}}^T)) \right) $$

$$ \frac{d(C_{\text{dil}})}{dt} = \frac{Q(C_{\text{dil}} - C_{\text{conc}})}{V_{\text{dil}}} \left( T \frac{F}{W} \frac{t_e}{J} + (L_W(C_{\text{conc}}^T - C_{\text{dil}}^T)) \right) $$

$$ \frac{dV_{\text{conc}}}{dt} = \left( T \frac{F}{W} \frac{t_e}{J} + (L_W(C_{\text{conc}}^T - C_{\text{dil}}^T)) \right) \frac{NA_m}{V_{W}} $$

$$ \frac{dV_{\text{dil}}}{dt} = \left( T \frac{F}{W} \frac{t_e}{J} - (L_W(C_{\text{conc}}^T - C_{\text{dil}}^T)) \right) \frac{NA_m}{V_{W}} $$

Where, $C_{\text{conc}}$ is concentration of hydrochloric acid (HCl) in concentrated compartment, $C_{\text{dil}}$ concentration of HCl in dilute compartment, $C_{\text{conc}}^T$ is concentration of HCl in concentrate tank; $C_{\text{dil}}^T$, concentration of HCl in dilute tank; $C_{Bf,C}$ and $C_{Bf,D}$, the concentration on the surface membranes in the sides of concentrate and dilute solutions, $D_a$ and $D_c$, the diffusion coefficient of HCl through anion exchange membranes and cation exchange membranes respectively; $F$, the Faraday constant; $J$, the current density; $I_a$ and $I_c$, the thickness of anion exchange membrane and cation exchange membrane respectively; $V_{\text{conc}}$, volume of solution in concentrate tank; $t_e$ and $t_a$ are the cation and anion transport number in the CEM and AEM; $D$, the concentration diffusion coefficient of acid through membranes, $l$ is the average thickness of membranes; $V_{\text{dil}}$, volume of solution in dilute tank; $N$, the number of cell; $V_{\text{comp}}$, the volume of compartments; $Q_{\text{dil}}$ and $Q_{\text{conc}}$, the flowrate of the dilute and concentrate solutions; $A$, active membrane area; $L_W$, the membrane constant for water transport by diffusion; $t_w$, the water transport number; $V_{W}$, molar volume of pure water.

2.1. Energy consumption in ED Process

The energy considered in this study is the electrical energy required to transfer ions from the dilute solution to the concentrate while the energy pumps which flow in the solution is neglected. This is because the pressure drop inside the ED stack for the laboratory scale is quite small. Electrical energy consumption (Ws) in this ED process is calculated with the following expression:
\[ W_{\text{elec}} = \int_0^f \left[ (ja_{\text{me}})^2 R_{\text{total}} + \left( E_{\text{el}} - (E_j + E_D)N \right) ja_{\text{me}} \right] dt \]  \hspace{1cm} (7)

where \( E_{\text{el}} \) is the electrode potentials for the anode and cathode processes; \( R_{\text{total}} \) is the overall resistance of the membranes, the bulk solutions, the boundary layers, and the electrode rinsing solutions and \( E_j \) and \( E_D \) are the overall junction and Donnan potential differences across the boundary layers and membranes pertaining to any cell respectively; \( N \) is the overall number of cells, each one composed of a couple of anionic and cationic membranes. The parameters of the ED process are adopted from work of Rohman [2].

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3. Dynamic multi-objective optimization techniques

The dynamic optimization method implemented in this study control vector parameterization, CVP. The control vector parameterization (CVP) method was using AMIGO2 package within MATLAB environment developed by Balsa-Canto et al [6]. The AMIGO2’s algorithm of CVP approach was adopted from Vassiliadis et al’s [7] work.

The basis of the CVP method is to parameterize the control trajectories and leave the state trajectories continuous. First, the ODE solver calculates the differential equation. Then, the original problem of dynamic optimization is transformed into the finite dimensional problem (NLP) for execution the static optimizer. Further, a suitable gradient method with a NLP type algorithm is needed. This corresponds to a ‘feasible’ path approach since the differential equations are satisfied at each step of the optimization. A piecewise-constant or piecewise -polynomial approximation of the inputs is often utilized. The basic procedure is as follows: 1) Parameterize the inputs using a finite number of decision variables (typically piecewise polynomials). The vector of decision variables also includes final time; 2) Choose an initial guess for the decision variables; 3) Integrate the system states to the final time and compute the performance index and the constraints; 4) Use an optimization algorithm, such as Sequential Quadratic Programming or Quasi-Newton methods to update the values of the decision variables; Repeat Steps 3-4 until the objective function is minimized.

3.1. Multi-objective optimization (MOO) technique

The optimal solution for MOOs is not a single solution as for single objective problems, but a set of solutions defined as Pareto-optimal solutions. A set is said to be a non-dominated set or Pareto-optimal set if it is not dominated by any other solution that belongs to the solution set. The Pareto-optimal set is
the best optimal solution for all objective functions if it is not possible to improve a given objective without deteriorating the value of another objective. Elitist Non-dominated Sorting GA or NSGA-II was one of widely used MOO procedures which were developed by Deb et al [8]. The NSGA-II implemented three features, i.e., elitist principle, explicit diversity preserving mechanism and non-dominated emphasizing. Here, the individuals in a population underwent non-dominated sorting, and individuals are given ranks based on this. A selection was done based on crowding distance (representing the neighbourhood density of a solution). To implement elitism, the parent and child population were combined and the non-dominated individuals from the combined population were propagated to the next generation. The next step included off-springs generating from the selected population using crossover and mutation operators. Finally, the present off-springs and population were sorted dependent upon the non-domination and only the best individuals with the number of the population size (P).

3.2. Problem optimization formulation

Concentration of sodium chloride solution in the concentrate and dilute tanks and volume of solution in the concentrate in dilute tanks were considered as states variables, whereas the control (decision variables) was current density. The objective function was to maximize the concentration of concentrate tank and to minimize the energy consumption. It is assumed that the objective function is of the form min function (to minimize). To maximize \( C_{\text{conc}} \), max function is expressed as: \( \min \left( C_{\text{conc}} \right) \). The inequality constraint associated was a product recovery percentage (PR). The final time was fixed at 5.5 hr. The dynamic optimization problem is shown as following:

\[
\min_{j(t), Q(t)} \phi_1 = \int_0^T \left[ (j a_{me})^2 R_{\text{total}} + \left( E_{el} - \left( E_j + E_D \right) N \right) j a_{me} \right] dt
\]

\[
\min_{j(t), Q(t)} \phi_2 = -C_{\text{conc}}^T
\]

Subject to: \( Mdx/dt = f(x(t), u(t), p(t)) \) (model equation);

\( 0.01 - \frac{C_{\text{conc}}^T}{1} \leq 0 \) (terminal constraints);

\( t_f = 5.5 \text{hr} \)

\( 0 \leq j \leq 0.5 \text{ A/cm}^2 \) (lower and upper bounds);

\( 0 \leq Q \leq 15 \text{ mL/s} \)

\( C_{\text{conc}}^T = C_{\text{conc}}^T = 1 \text{ mol/L} \)

with: \( V_{\text{conc}}^T = 2 \text{ L} \) (initial condition)

\( V_{\text{conc}}^T = 2 \text{ L} \)

4. Results and discussion

The Pareto-optimal front selected, i.e. NSGA-II, shown in Fig. 2 consists of three distinct zones. The lower end of the Pareto-optimal front (zone I) was characterized by relatively low acid concentration tank and energy consumed. On the other hand, the upper end of the Pareto-optimal front (zone III) was characterized by relatively high acid concentration tank and energy consumed. The intermediate zone (zone II) which was placed between zone I and zone II, was indicated as medium acid concentration tank and energy consumed. Since there is no report for MOO study in ED acid-sugar separation thus, a comparison study of MOO results could not be performed. Each point of the Pareto-optimal front in Fig 2 was correlated with different current density and flowrate profiles. The non-dominated points A, B and C which was located at zone I, zone II and zone III, respectively, had different trend trajectories, as shown in succession of Figs 3-5. Dynamic optimization
results for non-dominated points A, B and C which is comprised of two distinct ED performances such as energy consumption and acid concentration in the concentrate tank, are tabulated in Table.1.

![Figure 2. Pareto Front](image)

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### Table 1: Energy consumption and acid concentration in point A, B and C

| Non-dominated point | Point A | Point B | Point C |
|---------------------|---------|---------|---------|
| Energy consumption, Wh | 632.2 | 721.9 | 835.8 |
| Concentration in the concentrate tank, mol/L | 1.895 | 1.996 | 2.096 |

As shown in Table 1, the energy consumed for non-dominated points A, B and C was 632.2Wh, 721.9Wh and 835.8, respectively. While, the acid concentration in the concentrate tank achieved for non-dominated points A, B and C was 1.895 mol/L, 1.996 mol/L and 2.096 mol/L, successively. The control variable that has significant impact on energy consumption and acid concentration is current density. It is because the rate of ion migration through the membranes proportionally increased with current density and energy consumption is a power function of the current density applied [2]. Therefore, the different current density profiles produce variation amount of energy consumed and acid concentration as shown in Fig. 3a,4a and 5a. The point A produced the smallest energy consumption and acid concentration due to lowest value of the optimal current density trajectory obtained, and vice versa for the point C.
The optimal profiles of current density (Fig. 3a-5a) and flowrate (Figure 3b-5b) had opposite trend, but had complementary effect for supporting transfer ions. As current density profile decreased, the flowrate trajectory equilibrated to maintain ion transport by increasing flowrate. That obviously enhances the ion transport through the membranes which leads to increase the acid concentration. This is because a higher flowrate can reduce the thickness of the boundary layer. Consequently, the reduction of the thickness will lead to a small energetic barrier. Therefore, the thinned layer obtained can enhance the transfer ions and thus, increase the amount of acid concentration and decrease the amount of energy consumption [5].
The implementation of a PF analysis is dependent upon the availability of decision maker’s preferences. Since Pareto optimal solutions have different optimal trajectories, the inspection of the entire Pareto front helps the decision maker in deciding which specifications of the performance objective can be achieved and how the specifications could be traded off in order to find the most suitable operating condition for the ED process. The PF of NSGA-II obtained clearly opens a wide range of alternatives to the decision maker to operate the system based on practical and feasible consideration.
5. Conclusion
ED batch process typically has multiple performance objectives some of which conflicts with each other. The presence of multiple objectives in a problem usually gives emerge to a set of optimal solutions, commonly known as Pareto-optimal solutions. The elitist non-dominated sorting genetic algorithm or NSGA-II approaches have been applied to obtain the Pareto-optimal solutions for constrained multi objective optimization problems that are related to the energy consumption and acid concentration in the concentrate tank. Each point of Pareto front has different optimal current density and flowrate trajectories which lead to variation amount of energy consumption and acid concentration. The evolution
of the entire Pareto-optimal front can help the decision-maker visualize the trade-offs between different objectives, and select an appropriate operating condition for the process.

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