1.0 Introduction: Yeast Fermentation

Sugar + oxygen → yeast + CO₂ + alcohol

• *Saccharomyces cerevisiae* (aka baker’s yeast) - the most studied strain

• As the benchmark

• What we want? ---MORE YEAST!
  - Enhance the supply of raw material
  - Sustainable environment and production
  - Future potential
1.0 Introduction: Fed batch operation

**AIM:**
Maximize yeast
Minimize alcohol

**WHY Fed-batch?**

1. Dynamic growth behavior
2. Quality
3. Resource saving
2.0 Objective

- To introduce and apply the learning algorithm (Q-Learning) in fermentation system to determine the optimal substrate feeding profile

- To use the Q-Learning optimized profile as predetermined profile for fermentation system

Motivations:
- Unsupervised learning ability
- Reduction of human input
- Applicable to highly dynamic system
- Multi-objectives algorithm
3.0 Methodology

- Q-learning (QL) is an unsupervised learning algorithm
- Works by learning state-action function that gives expected reward of taking an action in a specific state with a fixed policy.

Observation and Learning Module

- QL can be described as the following equation:

\[ Q_t(s, a) = (1 - \alpha)Q_{t-1}(s, a) + \alpha[R_t + \gamma \max a' Q'(s', a')] \]

Where
\[ s = \text{state} \quad s' = \text{next state} \]
\[ a = \text{action} \quad a' = \text{next action} \]
\[ Q = \text{current Q-value} \quad Q' = \text{Expected Q-value in next state} \]
\[ t = \text{time} \quad \alpha = \text{learning rate} \]
\[ R = \text{reward} \quad \gamma = \text{discount factor} \]
3.0 Methodology

In this research, QL is used to:

• Observe and learn the effect of input feed flow rate on the various product concentration

• Maximum reward is chosen for the feed which gives maximum yeast and less alcohol

• Determine the optimal feed profile by total maximum reward.
4.0 Simulation

**Material Balances**

\[
\begin{align*}
\frac{dC_s}{dt} &= \frac{F}{V} (S_o - C_s) - \left( \frac{\mu}{Y_{x/s}} + \frac{Q_{e,pr}}{Y_{e/s}} + Q_{in} \right) C_x \\
\frac{dC_x}{dt} &= -Q_o C_x + k_L a_o (C_{o}^e - C_o) - \frac{F}{V} C_o \\
\frac{dC_e}{dt} &= (Q_{e,pr} - Q_{e,ox}) C_x - \frac{F}{V} C_e \\
\frac{dC_R}{dt} &= \mu C_x - \frac{F}{V} C_x \\
\frac{dV}{dt} &= F
\end{align*}
\]

- Complex process dynamics
- Substrate and product inhibition

**Dynamic**

**Kinetic**

- \( Q_s \)
- \( Q_{S,e} \)
- \( Q_{S,ox} \)
- \( Q_{S,red} \)
- \( Q_o \)
- \( Q_{Q,lim} \)
- \( Q_{Q,ox} \)
- \( Q_{e,pr} \)
- \( Q_{e,ox} \)
- \( \mu \)
- \( RQ \)
- \( Q_o \)
- \( Q_c \)
5.0 Results and Discussion

Nominal exponential feeding (EF) performances: \( F = 500e^{0.05t} \)

Q-learning (QL) optimized feeding performances

Comparison of substrate (glucose), undesirable products (ethanol) and biomass (yeast) concentrations for exponential feeding and Q-learning feeding strategy.
5.0 Results and Discussion

QL manage to optimize feed flow rate to the maximum before inhibitions and overflow metabolism which triggers ethanol production happens.
5.0 Results and Discussion

QL-suggested feeding profile is able to achieve multi-objective purposes: reduce substrate usage, maximize yeast production and minimize ethanol.
6.0 Conclusion

Based on the performances, Q-learning is able to:

- suggest satisfying optimal profile as predetermined feeding strategy for yeast fermentation based on its objectives;
- act in dynamic-complex system;
- suggest an alternative algorithm for biosystem...