Dealing with Uncertainties Arising from Environmental Conscious Multi-Objective Optimization

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Abstract
Process optimisation has been at the core of design and retrofit of process industries. Traditional process design focuses on plant operations to minimise costs or maximise profits using performance indicators of conversion, yields, efficiency, and productivity. With dwindling resources coupled with environmental degradation, environmental objectives started to be incorporated into the optimisation, through strategies such as waste minimisation and pollution prevention. While environmental conscious design has benefited from life cycle assessment in finding the environmental burdens of a process, it generates a multi-objective optimisation problem with many variables and constraints. Mathematical programming provides a solution in the form of Pareto front, though to find a compromised solution remains a difficult task. Furthermore, the incorporation of environmental indicators brings in a considerable number of uncertainty sources that exacerbate the difficulties of optimization. These reflect both on economic costs and environmental conditions. In this paper, the progress and framework of incorporating LCA results with process design and optimisation is given followed by a discussion of barriers, with the emphases on uncertainty issue. A case study on enhanced oil recovery from a reservoir using CO₂ is carried out to highlight the effect of uncertainties in one of the external index to the optimisation results.

Keywords: Multi-objective optimization, Uncertainty, Environmental modeling, EOR

1. Introduction
Process optimisation has played an important role in the design and modification of chemical and process industries. Traditionally, the main objective of optimisation is economic considerations where the set aim is the minimisation of production costs thereby maximising profits. However, at the onset of the 1990s and with the global warming awareness, environmental factors initially based on legislative constraints became necessary to be incorporated into the optimisation. The development of environmental objective use in optimisation is shown in Figure 1.

Figure 1. Environmental conscious design
Cost minimisation considers economy and technology as basic inputs of design (e.g. material selection). The waste minimisation objective is deployed through the selection of alternative process routes and also through recycling to reduce wastes. Waste minimisation objectives and techniques have been normally influenced by government legislation. The reactive responses of companies meant end pipe solutions were always sought to meet set requirements. However, due to the sporadic nature of the ever changing and stringent government legislation coupled with exorbitant end of pipe solutions, the process industries had to rethink of their approach from scratch. This is where pollution prevention techniques were developed.

Introducing pollution reduction objectives in design and optimization saw the innovation of new technologies which were mostly add-ons to existing facilities, or retrofitting of existing operations and units. However, end pipe techniques and re-design are all short term strategies for environmental compliance. To conduct a conceptual design for a sustainable plant remains a long term strategy. One of the advances is to incorporate Life Cycle Assessment (LCA) results in the problem formulation stage. LCA considers all environmental aspects of a product, from the raw material, production, end use, to waste generation, reuse and disposal. Despite the benefits of LCA in finding the environmental loads/burdens of a process and alternatives, its major deficiency is the fact that the study does not have a set methodology or principle approach for selection of the most ideal alternative process to meet set standards while appeasing the decision makers’ preferences (Guillén-Gosálbez et al., 2008). Therefore, mathematical tools for optimisation have been used to aid LCA meet its deficiency and increase its superiority in environmental conscious process selection and design.

While environmental conscious design has benefited from life cycle assessment in finding the environmental burdens of a process, it generates a multi-objective (MO) optimisation problem with many variables and constraints. It has been recognised that there are various barriers of current LCA study, such as data reliability; inventory analysis difficulties; temporal and spatial characteristic incorporation, etc (Finnveden et al., 2009; Pennington et al., 2004). Such drawbacks inevitably affect the reliability of optimisation if the LCA results are to be used. The aspects under consideration can be:

- The characteristic of optimisation problems (complexity of the problem)
- The algorithms for multi-objective optimisation (solution procedure)
- The trade-off of optimum solutions (economic-environmental variables)
- Treatment of uncertainties

Incorporation of environmental indicators brings in a considerable number of uncertainty sources that exacerbate the difficulties of optimization. Classification of uncertainties can be grouped into two (Li et al., 2009): (a) External uncertainties related to physical factors of plant streams, material supply, costs, environment, etc. and (b) Internal uncertainties related to missing process parameters or information. The latter classification mainly dealing with process design has borne the lion’s share of focus and optimization strategies for the former are now being incorporated. Taking the environmental conditions as an example, it is not easy to predict current situations let alone the future conditions in terms of environmental indicators obtained from the LCA study like eco-toxicity. Instead, data for such is always depicted and input as an assumption on average findings. In reality such data could vary considerably, especially with time and location.
2. Problem Description in a Case of EOT

In this case study, we will show how the uncertainty in the oil price affects the optimization results. The case chosen is for CO\(_2\) enhanced oil recovery, which aids in the retrieval of extra oil that would otherwise be un-exploitable with current conventional technologies. A stream of CO\(_2\) is injected in an oil reservoir at a determined miscible pressure that enables mixing of the CO\(_2\) with oil. The CO\(_2\) displaces oil held in the pores of reservoir basin rocks while increasing the surface volume of remaining oil thereby making it easy to be extracted while CO\(_2\) remains sequestered within the basin. With the CO\(_2\) emissions are regulated, oil producers will be benefit from sequestration by this technology.

A model was developed by Leach et al. (2011), relating the rates of CO\(_2\) injection rate to the oil recovery through material balance and formulated. The model incorporated the environmental burdens from combustion of a barrel of oil into an incidence parameter \(\beta\), which was then incorporated as a scalar function to the main objective function to yield a multi-objective aggregated single environ-economic objective function. Use of aggregated MO optimization in the selected case study is performed due to its simplicity and relatively justifiable results. The problem after aggregation is described as following.

Maximize:

\[ \pi = [(p - \beta r) - (\omega_m - \tau - \omega_r)C](0.06 + 0.2C - 0.16C^2)R(t) - w_C - F \]

Subject to:

\[ R(0) = C(0) = 0.4851; 0 \leq C \leq 1; R \geq 0 \]

State equation:

\[ \dot{R} = -(0.06 + 0.2C - 0.16C^2)R(t) \]

Where, \(\pi\) is the profit, \(p\) the oil price, \(\tau\) the carbon tax per barrel of oil, \(\omega_m\) the purchase cost of CO\(_2\), \(\omega_r\) the cost of recycling CO\(_2\), \(C\) the injection rate of CO\(_2\), \(R\) the amount of recoverable oil, \(F\) the annualised expenses, and \(\beta\) is a constant relating the environmental factors of CO\(_2\) from combustion of a barrel of oil, to its avoided release.

The objective is to find the optimum CO\(_2\) injection rate \(C\) to maximise the profit. There are two external factors that have large uncertainties: the oil price and the carbon tax. Figure 2 shows the middle year oil prices for the last 30 years. If simulation is conducted by simply setting the two factors at some certain values throughout the time span, as done by the report, the accuracy of optimization solutions is in doubt. This kind of irregular fluctuation will also be expected in future. It is where the challenge of optimization with uncertainty lies.
3. Uncertainty Analysis

To demonstrate the effect of uncertainty caused by oil price, the optimization is carried out at a fixed carbon tax of $4 (per equivalent oil barrel), with oil reserves in the analysed reservoir set to 1 million barrels of oil. The other parameters are set as (Leach et al., 2011): $\beta = 2.2; \tau = 4; \omega_m = 4; \omega_r = 1; F = 1$.

According to EIA (2011), the predicted oil price for the next 25 years represents an average increase of 2.6% per annum (Figure 3a). A lower projection of -0.8% average oil price decrease and higher projection of 4.6% average oil price increase have also been predicted with the reference of 2.6% increase. In corresponding to these predictions, the optimisation is performed for (a) the price set at its medium of $130 over the entire period; (b) lower projection; (c) reference case; (d) higher projection. The results are shown in Figure 3b, 3c and 3d.

CO$_2$ injection as shown in Figure 3b is enhanced with higher oil prices as the expenses of increasing CO$_2$ injection are countered with higher returns. This is reflected in Figure 3d where the increased CO$_2$ injection aids in recovery of more oil, which yields better profits with higher oil prices. This fact also increases the project life of the oil recovery from the improved earnings of higher oil prices.

The average decrease in oil price reflected in the red mark of Figures 3b and 3c further prove that lower oil prices induce lower CO$_2$ injection which not only affects the profit but also on the duration of oil recovery. Although only oil price was considered for ease
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as a demonstration of uncertainty due to its inelastic price value, its significant is not only on profits from the oil recovery but on CO\textsubscript{2} sequestration as well. Higher oil prices entail the use of more CO\textsubscript{2} which in the long run increases the sequestration of the same as more CO\textsubscript{2} is exposed to the oil reservoir basin allowing it to seep more into the reservoir rock pores and react with basaltic rocks to form carbonates or remain transfixed in the reservoir rock pores.

4. Discussion and Conclusion

A simple case study of an enhanced oil recovery project has shown that not only does the optimal path of CO\textsubscript{2} injection vary largely with the oil price, but it is also difficult to quantify. As evidenced by history record, the price of oil is highly uncertain as it is affected by many events such as policies, wars, world economics, strength of the dollar, etc. Forecast projections from organisations such as EIA also show a wide variability, and are based mainly on economic prospects. In fact, there is no accurate model to predict the future oil prices. The uncertain of oil prices implies limitation in the optimal CO\textsubscript{2} trajectory path found, which might be used for future material inventories scheduling and related investments planning. The oil recovery project is either under or over-stated in the use of CO\textsubscript{2} injection. As a result, the discrepancies could not only eat into profits but compromise the viability of such a project, especially in the former case.

The current approaches for uncertainty have focused on linear models where uncertainty relationship can be linked from input to output. One of the proposals employed to cater for uncertainty is the use of penalty functions in the algorithms but this is mostly based on mean results from statistical regression. The drawback of this is that uncertainty in reality does not conform to its mean thereby warranting the dependability of penalty functions. Moreover, uncertainties are not always linear and this causes difficulties in accounting for their effects on outcomes when they are non-linear. Although strategies have been put forward to aid optimisation with uncertainties, such as, the stochastic programming, fuzzy programming and stochastic dynamic programming, it remains a challenge when price factors are taken into account.

References


