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A Comprehensive Analysis of the Determinants of Swap Problem in the Supply Chain of the Petroleum Industry

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Abstract

Applying mathematical modeling to solve swap problems, specifically in the petroleum industry, have proven to help the decision makers to better determine what, where, and how much to swap in order to reduce supply chain (SC) costs and improve its surplus. However, for a better determination of the alternatives and a more profound evaluation of the tradeoffs among them, a comprehensive analysis of the results and a thorough investigation of their impact on the parties involved in swap are crucial. This research performs a detailed sensitivity analysis of the swap problem to examine the effect of different operational parameters on the cost savings realized along the supply chain of the organizations involved in swap. Findings of this study suggest that, if performed properly, swap can significantly reduce supply chain costs and may result in substantial savings, creating a win-win situation for all parties engaged in swap.

Keywords: Supply chain management, the swap practice, mathematical modeling, sensitivity analysis, petrochemicals industry.

1. Introduction

Swap transactions among same-level supply chain partners, specifically in the petroleum industry (where suppliers are scattered in distant geographical locations), can offer companies great cost savings. However, making decisions in such collaborations can be very complicated. Swapping commodities with other organizations (even with competitors) can drastically shrink transportation costs and reduce risks in comparison to shipping goods long distances to internationally remote locations. Despite the massive advantages, companies which have adopted the swap practice are still not reaping the complete savings that can be had through swap practices.

Al-Hussain et al. (2006) argue that one reason companies are not getting full savings benefits is because decisions surrounding swaps between two companies are often solely made using judgmental approaches and spreadsheets. Al-Hussain et al. (2008) proposed a mixed integer programming (MIP) model to provide a comprehensive analysis of the swap practice. The model included its limitations and strengths. Two earlier studies used linear programming (Khorramshahgol et al., 2010) and Goal Programming (Khorramshahgol et al., 2014) to help SC designers and managers better decide on what, where, and how much to swap with competitors. Results of these latter two studies show that the use of systematic approaches (such as mathematical modeling) to swap practices outperform the judgmental approaches currently in use. This can result in an increased savings of about 20% for companies involved in swap.

Most practitioners completely ignore sensitivity analysis (SA) when using mathematical programming models. Often, mathematical optimization methods are constructed that incorporate unchanging (rigid) constraints and which use the results of the static models for solving dynamic problems (such as the ones presented in any supply chain management (SCM). The basic idea in sensitivity analysis is to change the model and observe its results (Kleijnen, 1992). In practice the decision maker determines what to vary and what to observe (Eschenbach, et al. 1989; Eschenbach et al. 1990; French 1992).

The dynamic nature of SCM mandates performing SA as the first step in post optimality analysis (Belvardi, et al, 2012, Li, et al, 2016). Several very recent studies have incorporated sensitivity analysis into SCM decision analysis (Kim et al., 2014; Ameda, 2014; Zheng et al., 2016).

In this paper, a comprehensive investigation of swap problem in the oil industry is provided, considering factors such as demand pattern, production capacity, volume owed, sharing periodicity, price pattern, and their interactions. This research highlights some managerial aspects of the swap practice in order to help SC designers and managers fully utilize the potential benefits that swap practices can offer.

2. Methodology

Two earlier studies (Khorramshahgol et al., 2010; Khorramshahgol et al., 2014), offered models based on linear programming (LP) and goal programming (GP) to solve the swap problems for two petrochemicals companies (named A and B). This paper investigates the sensitivity of the results of the swap analysis (from the two earlier research studies) due to changes in demand pattern, production capacity, volume owed, sharing periodicity (τ), and rice pattern. Table 1 shows the variation in parameters and their relative values.

Table 1. Parameters to be varied in the Sensitivity Analysis and their Relative Values

Parameters	Variation of Parameters	Num. of Levels
Demand	Base Case Increasing Decreasing Cyclic	4
Production Capacity	Unconstrained Constrained: Average of Max. demand + 20% capacity cushion 10% capacity cushion	3
Volume Owed (VO)	Unconstrained 6000 MT 3000 MT	3
Sharing Periodicity τ	Every period Quarterly Twice a year	3
Price of Commodity	$450 (at the time of this study) Increasing Decreasing Cyclic	4

The parameters shown in Table 1 were determined by the authors and the SC directors in two companies from petrochemical industry (for anonymity, we refer to them as Company A and Company B). These parameters are those believed either to have the greatest potential for variation and are uncontrolled by firms, (e.g., demand and price patterns of commodity), or those that can possibly be controlled by firms (e.g., production capacity, volume owed, and τ). Nonetheless, both groups when varied can have significant effects on cost savings.

The demand for each company (A and B) is used to generate three different demand patterns (increasing, decreasing, and cyclic) for that company. For example, the increasing demand patterns for both companies are generated such that demand starts from the minimum demand value detected in the case, then increases for 20 periods until the sum of the generated demand is equal to the sum of the actual demand in the case. The decreasing and cyclic demand patterns are generated in a similar fashion.

In addition, information such as the minimum, maximum, average, and the range of the actual price of the commodity under study (i.e., Mono Ethylene Glycol—MEG) during the same time period in the case is used to generate three different price patterns (increasing, decreasing, and cyclic).

Since the current model is designed to handle one type of commodity at a time, it is reasonable to assume that the demand and price patterns are the same for both companies during any swap period. For example, if Company A's demand pattern increases while the price pattern is cyclic, then the same is assumed to be true for Company B's demand and price patterns.

It is important to mention, however, that although prices and demand are closely related in most industries, oil and petrochemicals have a very low price elasticity of demand. In other words, prices have to soar considerably to affect demand even a little (Anon, 2002). The short-run demand is therefore inelastic because petroleum plays a critical role in today's economy. Thus, the price elasticity of demand's effect is ignored in this study and price variation is assumed to have no influence on demand values.

In order to test the effect of production capacity on supply chain savings, production capacity is constrained to two levels:

(1) The average of both companies' maximum demand plus 20% of the capacity cushion:

(16,413MT x 0.2) + 16,413MT = 19,695MT, and

(2) The average of both companies' maximum demand plus 10% of the capacity cushion:

(16,413MT x 0.1) + 16,413MT = 18,054MT.

Since the model does not allow lost sales or backorders, assuring that all demands are met is necessary in order to obtain a feasible solution. As the production capacity of both companies is assumed to be equal, an average of the maximum demand of both companies is used.

Based on Table 1, there are (4)(3)(3)(3)(4) = 432 different scenarios in the sensitivity analysis case. Since the result of each scenario represents an optimal solution based on the given values of the parameters, it is not only desired to find which scenario will result in the best optimal solution and maximum savings, but also to observe the behavior of the swap model under the interaction of the variation of the operational parameters provided in Table 1. Accordingly, regression analysis is applied to explore the relationship between the parameters and their effect on supply chain savings. It is recommended that prior to conducting a regression analysis, unit root test of the variables be conducted to determine the stationary property of the variables (Sahin, et al. 2008).

Applying sensitivity analysis to the case is expected to provide further insight into the swap practice. It can help managers make better decisions regarding a swap agreement when parameters are expected to change. It can also help managers avoid negative consequences when market performance is poor.

3. Results

In order to evaluate the impact of operational parameters on supply chain savings, regression analysis was performed. Supply chain savings represents the dependent variable, and the independent variables are represented by the following operational parameters and interaction terms:

Demand pattern; Capacity constraints; Volume owed (VO) constraints; Sharing periodicity (τ);

Price pattern; Interaction of demand pattern and capacity constraints; Interaction of demand pattern and VO; Interaction of demand pattern and τ; Interaction of demand pattern and price pattern; Interaction of capacity constraints and VO; Interaction of capacity constraints and τ; Interaction of capacity constraints and price pattern; Interaction of VO and τ; Interaction of VO and price pattern;

Interaction τ and price pattern

The estimated regression equation, along with the standard error of estimation, the coefficient of determination R-square, and the adjusted R-square are:

Savings = 802639 + 45735 Demand + 0.034 Capacity + 13.7 VO – 48367 τ- 2379 Price - 0.0108 Dem.Cap – 6.09 Dem.VO + 5496 Dem. τ+ 406 Dem.Price +0.000002 Cap.VO – 0.0017 Cap. τ– 0.0001 Cap.Price + 3.48 VO. τ+ 0.184 VO.Price – 250 τ.Price

S = 37314 R-Sq = 72.1% R-Sq(adj) = 71.1%

The regression coefficients, their related standard error, t-value, and p-value are shown in Table 2 and Table 3 provides the analysis of variance.

Table 2. The Regression Analysis Coefficients

Predictor	Coefficient	SE Coefficient	T	P
Constant	802639	22575	35.55	0.000
Demand	45735	6209	7.37	0.000
Capacity	0.034	0.2019	0.17	0.866
VO	13.677	2.431	5.63	0.000
τ	-48367	3636	-13.3	0.000
Price	-2379	6209	-0.38	0.702
Dem.Cap	-0.01077	0.04198	-0.26	0.798
Dem.VO	-6.0947	0.56	-10.88	0.000
Dem.τ	5495.7	781.4	7.03	0.000
Dem.Price	406	1436	0.28	0.778
Cap.VO	0.00000151	0.00001637	0.09	0.926
Cap.τ	-0.00169	0.02284	-0.07	0.941
Cap.Price	-0.00006	0.04198	0	0.999
VO.τ	3.4826	0.3047	11.43	0.000
VO.Price	0.1842	0.56	0.33	0.742
τ.Price	-249.9	781.4	-0.32	0.749

Table 3. Analysis of Variance

Source	DF	SS	MS	F	P
Regression	15	1.5001E+12	1.00E+11	71.83	0.000
Residual Error	416	5.79199E+11	1392305284		
Total	431	2.0793E+12			

The coefficients of determination (R2), the adjusted R2, the F-statistics, and its associated p-value all suggest a very good fit in the swap model. The adjusted R2 measure indicates that the independent variables accounted for 71% of the total variation in the supply chain cost savings. Moreover, the F-statistic of 71.83 and its associated p-value of 0.000 imply that the swap model is highly significant. This means that the null hypothesis which states that there is no relationship between the dependent and any independent variables" can be rejected. Moreover, Table 2 indicates that not all operational parameters are statistically significant and that some operational parameters' impact is overruled by their significant interaction effect with other parameters.

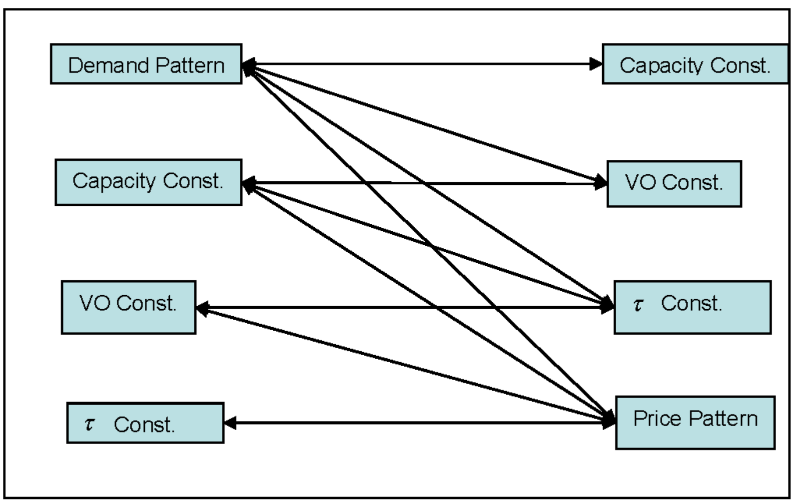

Figure 1. Interaction Terms Used in the Regression Analysis

3.1 Impact of the Interaction Terms

All possible two-way interactions between the independent variables are tested in the regression analysis, as indicated in Figure 1. The inclusion of such interaction terms helps explain more about the behavior of the swap practice. However, not every interaction term proved to be significant in the model. Therefore, only the significant interaction terms will be discussed next.

3.1.1 The Interaction Effect of the Demand Pattern and the Volume Owed

The coefficient of the demand pattern and VO interaction term in the regression equation, along with its t-value and p-value in Table 2 suggest that such interaction is statistically significant. This is evident in the example shown in Figure 2.

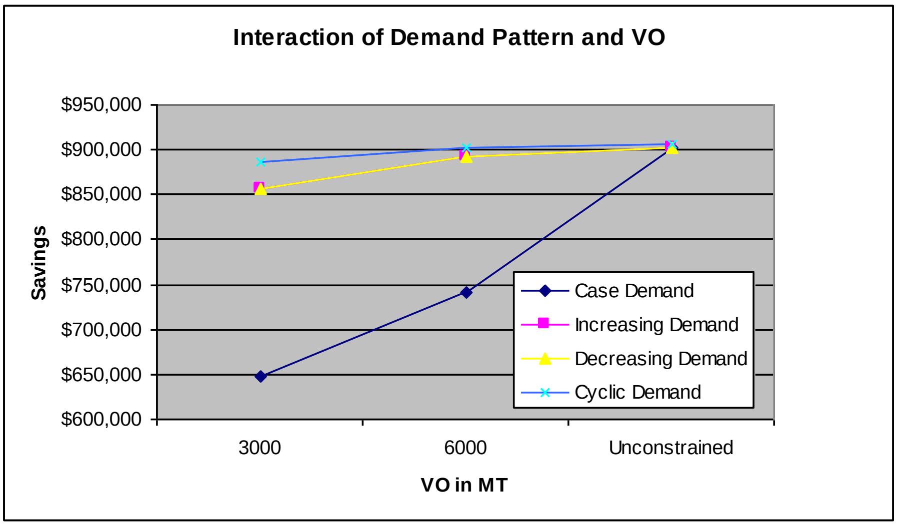

Figure 2. Interaction of Demand Pattern and Volume Owed

Results indicate that different demand patterns generate different savings under the same value of VO. Hence, constraining the value of VO before considering the demand pattern can eliminate chances of higher savings. For example, constraining the value of VO to 3000 Metric Tons (MT) per swap when the demand pattern is increasing generates $856,426 of savings. On the other hand, if the demand pattern is as given in the case, then constraining the value of VO to 3000 MT per swap reduces savings to $648,268. Therefore, before constraining the value of VO to any specified volume per swap, decision makers should first take into consideration the demand pattern.

It is also important to note that as the value of VO increases, savings also increase for all demand patterns. This is due to the fact that when the value of VO is constrained; the opportunities to swap are reduced, which means there are fewer chances to increase savings. The demand pattern of the case appears to have the lowest savings among all demand patterns under all values of VO. However, as the value of VO increases, a percentage increase in the supply chain savings of the demand pattern is the highest among all demand patterns. For example, a supply chain savings of the demand pattern increased by 14% when the value of VO increased from 3000 MT to 6000 MT per swap. On the other hand, the average percentage in supply chain savings increased by about 3.4% for all other demand patterns when the value of VO increased from 3000 MT to 6000 MT per swap.

At the time of this research, Companies A and B were pushing toward constraining the VO to 3000 MT per period. According to the output of the model, this is the lowest attainable savings among options ($648,268), and hence not the best decision to make. Therefore, companies planning to participate in a swap agreement and seeking maximum savings are urged to relax the value of VO as much as possible in order to fully utilize the savings opportunities offered by the swap practice.

3.1.2 The Interaction Effect of the Demand Pattern and the Sharing Periodicity τ

The coefficient of the demand pattern and the sharing periodicity interaction term in the regression equation, along with its t-value and p-value (Table 2), suggest that such an interaction is statistically significant. Figure 3 shows the effect of the interaction of demand patterns and τ on supply chain savings.

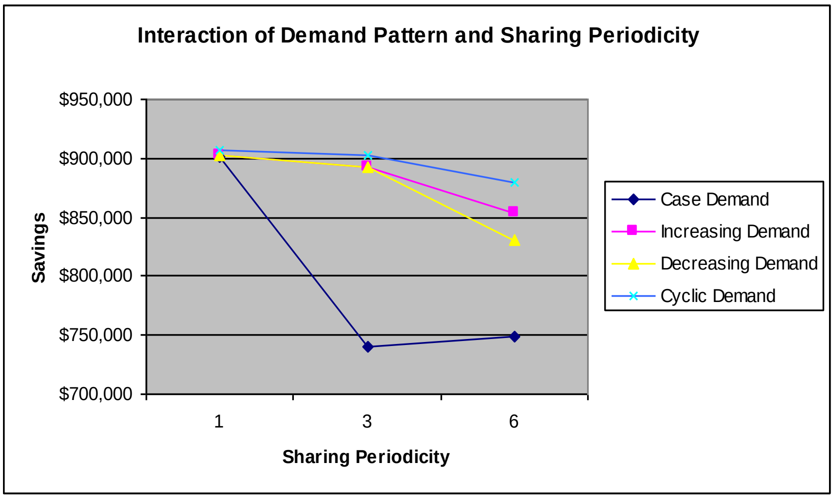

Figure 3. Interaction Effect of Demand Pattern and Sharing Periodicity

When the value of τ is set to one period, supply chain savings are at a maximum and relatively equal for all demand patterns. Then the supply chain savings are reduced as the value of τ is increased to three and six periods. Again, the demand pattern of the case is the most sensitive among all other demand patterns when τ is increased from 1 to 3 periods. The demand pattern of this case resulted in an 18% decrease in supply chain savings while the average decrease of supply chain savings for all other demand patterns was about 0.09%.

It is first expected that supply chain savings will always decrease as τ increases for all demand patterns. In other words, a higher sharing periodicity will always result in lower savings, regardless of the demand pattern. However, the results show that this is not generally the case. While the generated demand patterns (increasing, decreasing, and cyclic) all resulted in decreased supply chain savings as τ increased, the demand pattern of the case exhibited a unique phenomenon. Unlike the rest of the demand patterns, the demand pattern generated higher supply chain savings when τ was set to six periods than the case when τ was set to three periods. In fact, the supply chain savings actually tended to alternate depending on the demand pattern as the value of τ increased. This phenomenon, when tested on the demand pattern of the case, is shown in Figure 4. From the data we can conclude that a higher sharing periodicity does not always generate lower supply chain savings for demand patterns.

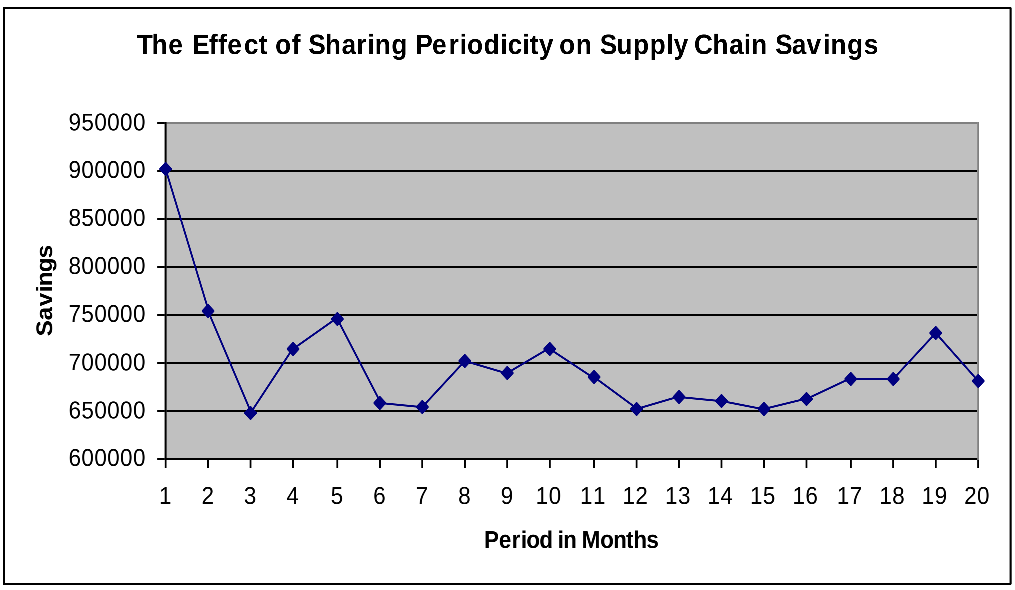

Figure 4. The Effect of Sharing Periodicity on Supply Chain Savings

Currently, companies involved in the study share their supply chain savings every quarter. According to the results, this value of τ generates the lowest supply chain savings versus the cases when τ is set to 1 or 6 periods. Therefore, companies interested in undergoing a swap agreement are urged to share their supply chain savings every period. If this is not possible, then based on their demand patterns, companies should first test the effect of all possible scenarios of τ on supply chain savings, as in Figure 4, then implement the best τ possible.

3.1.3 The Interaction Effect of the Volume Owed and the Sharing Periodicity τ

The regression analysis output implies that the effect of the interaction of the VO and τ on cost savings is statistically significant. Figure 5 illustrates the interaction effect and its impact on supply chain savings.

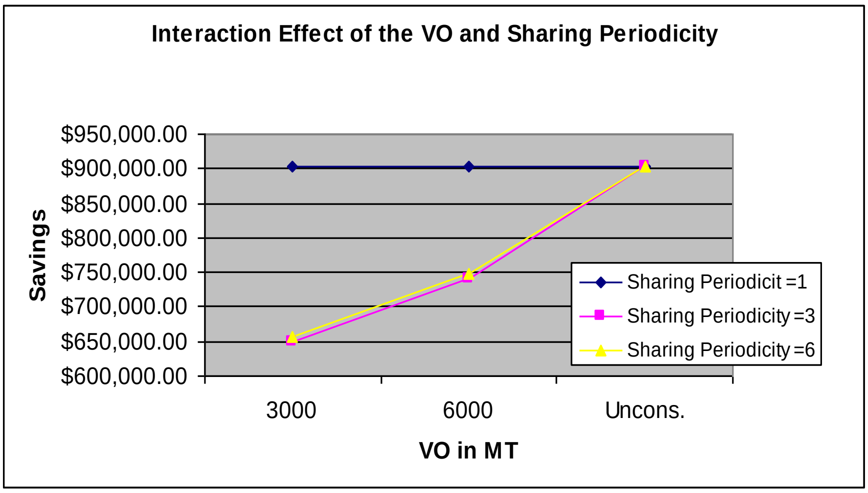

Figure 5. Interaction Effect of the VO and Sharing Periodicity

When τ is set to 1 period, supply chain savings are unaffected by the changes in the value of VO. This is a rational finding, considering the fact that no matter how much volume the companies owe each other, the opportunity costs of the volume owed by one company is neutralized by the opportunity of savings gained by the other, and hence should have no impact on savings. This remains true as long as the opportunities of costs/savings are instantly shared. When τ is set to 3 or 6 periods, supply chain savings are dramatically affected with changes in the value of VO. However, there seems to be a small difference in supply chain savings when τ is set to 3 and 6 periods for the VO values of 3000 and 6000 MT per swap. In addition, supply chain savings converge at the same value when VO is unconstrained. Thus, the value of τ has no impact on supply chain savings when VO is unconstrained.

Therefore, companies interested in undergoing a swap agreement can experiment with the sharing periodicity and volume owed parameters' values to reach their best option. For example, if companies must constrain the value of VO to 3000 MT per swap, then τ should be set to 1 period to gain maximum savings. In contrast, if τ must be set to other values, such as 3 periods, then the value of VO should be unconstrained, or as relaxed as possible in order to maximize savings.

3.2 Impact of Individual Parameters

3.2.1 Impact of the Production Capacity Constraints

The regression analysis output suggests that the effect of production capacity constraints has no statistical significance on supply chain savings. The value of the capacity coefficient of 0.034 is very small with a t-value of 0.17 and an associated p-value of 0.866. Figure 6 shows the average supply chain savings under different capacity constraints values.

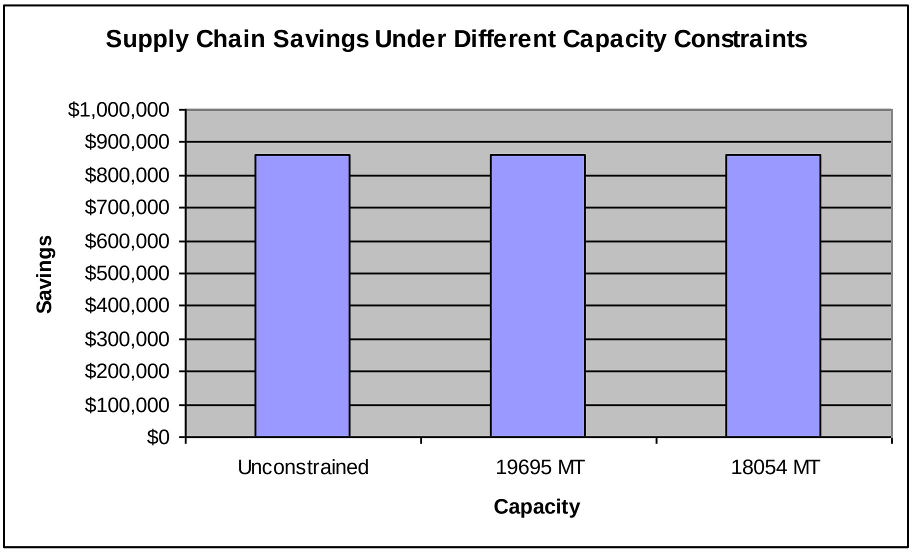

Figure 6. Supply Chain Savings under Different Values of Capacity Constraints

Nevertheless, the result on the significance of capacity constraints on supply chain savings is not conclusive. In general, the less production capacity available, the fewer commodities there are to meet the supply chain partner's demand, and hence opportunities to swap and save in transportation costs are eliminated. However, because the swap model does not take into account lost sales or backorders, the levels of production capacity used in the sensitivity analysis are always enough to meet customer demands. Otherwise an infeasible solution is obtained. In order to obtain further insight into the significance of production capacity, a model is required that can take into account lost sales or backorders.

3.2.2 Impact of the Price Pattern

Although results suggest that in some scenarios different price patterns result in different supply chain savings, the regression analysis output implies that the general effect of a price pattern on supply chain savings is statistically insignificant (p-value = 0.702). This is because the differences in supply chain savings (as a result of different price patterns) are relatively small when patterns averaged over all of the supply chain savings with all different prices. The formulation of the model also takes into account the price value when the amount to be paid back to each company is calculated. In fact, the swap agreement between companies is solely based on volume, ignoring the effect of prices variation. Hence, this result supports their strategy. Figure 7 shows the average supply chain savings when different price patterns are applied to the model.

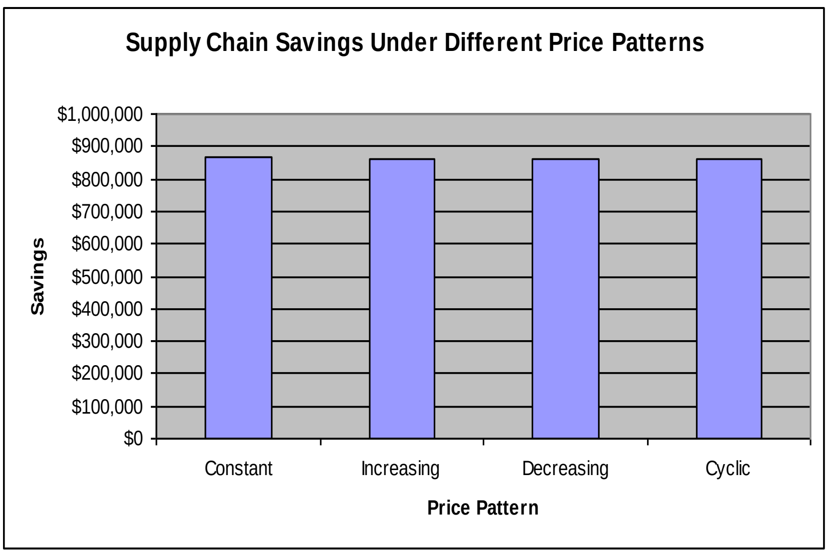

Figure7. Supply Chain Savings under Different Price Patterns

3.2.3 Impact of the Demand Pattern

According to the regression analysis output, the demand pattern is statistically significant. The demand pattern has the second largest coefficient in magnitude ($45,735). The t-value for the demand pattern is 7.37 with an associated p-value of 0.000. Hence, the demand pattern has a significant effect on supply chain savings in the swap model. Figure 8 shows the effect of different demand patterns on supply chain savings.

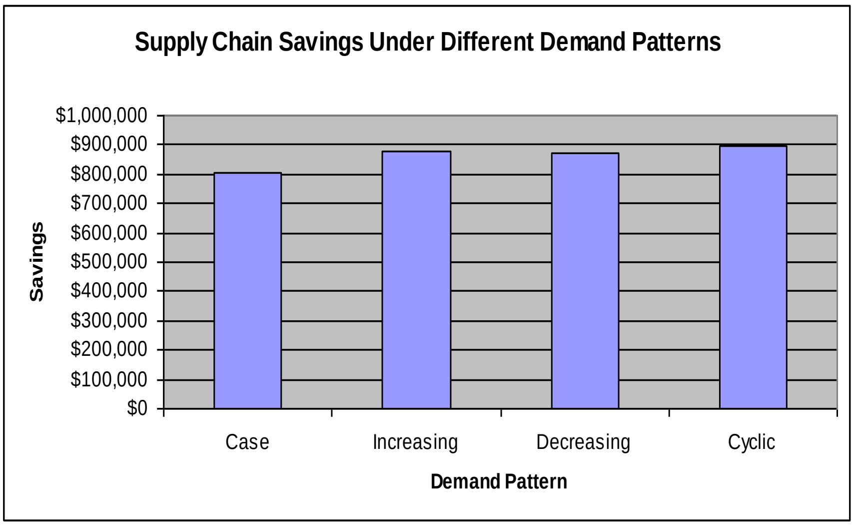

Figure 8. Supply Chain Savings under Different Demand Patterns

The swap model generates the greatest savings under the cyclic demand pattern when all other parameters are constant across all other demand patterns. However, although the swap model generates the most savings when the demand pattern is cyclic, other operational parameters, such as VO and sharing periodicity, influence the magnitude of the savings. This is also due to the significant interaction effect that the demand pattern has on these parameters. Therefore, for an accurate interpretation of the effects of demand pattern on supply chain savings, the interaction effects of a demand pattern with the VO and sharing periodicity need to be taken into consideration.

3.2.4 Impact of the Volume Owed Constraints

The regression analysis coefficient, t-value, and p-value for VO are 13.677, 5.63, and 0.000 respectively. The t-value and the p-value suggest that the effect of such parameters on supply chain savings is significant indeed. Figure 9 shows the average supply chain savings under different levels of the volume owed per swap between supply chain partners.

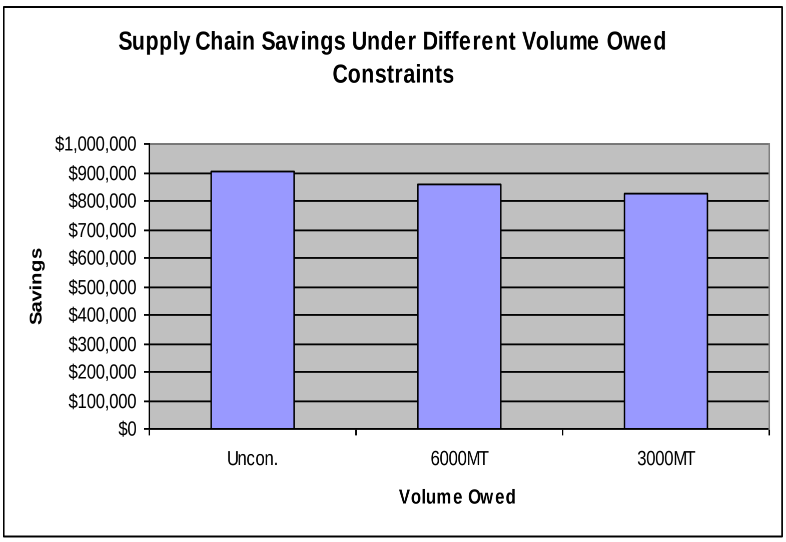

Figure 9. Supply Chain Savings under Different Volume Owed Constraints

The VO is the difference of total expenditures between supply chain partners when serving each other's customers in terms of volume. Hence, the higher the VO value, the more volumes may be swapped, and the more savings are generated.

On average, the differences in supply chain savings when using different levels of VO constraints is negligible relative to the overall savings. But, VO constraints possess a significant effect on supply chain savings due to their significant interaction effect with demand pattern and sharing periodicity, as discussed earlier. An accurate interpretation of the VO constraints need to be taken into account when considering the interaction effect.

3.2.5 Impact of the Sharing Periodicity (τ)

The variation of the value of sharing periodicity (τ) has the highest impact on supply chain savings. This is evident in the regression analysis output in Table 2. The coefficient of the sharing periodicity is the highest in magnitude among all other coefficients (-$48,367) for the values of τ tested (1, 3, and 6 periods). The t-value and the p-value of -13.30 and 0.000 respectively suggest that the effect is statistically significant. Figure 10 shows the average supply chain savings under different sharing periodicity values.

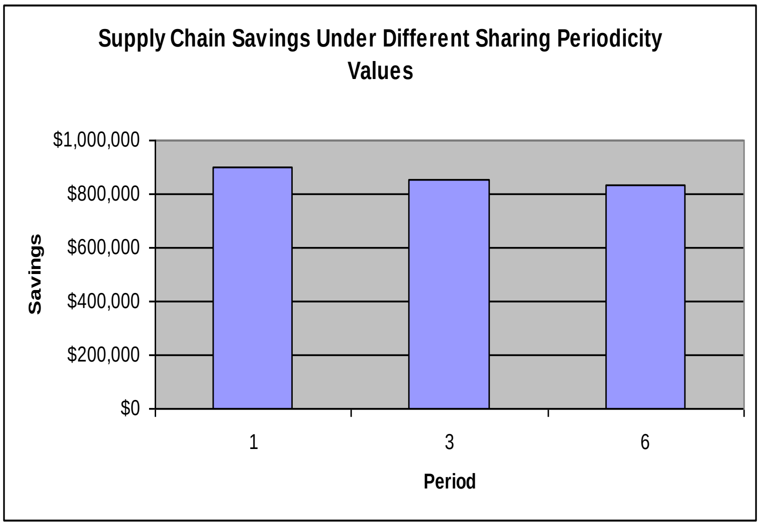

Figure 10. Supply Chain Savings under Different Levels of Sharing Periodicity

Although the values of τ tested in the sensitivity analysis show that on average, supply chain savings decrease as τ increases, this is not a conclusive result. Figure 11 shows that a trend of supply chain savings when τ increases or decreases does not exist. Hence, companies interested in undergoing a swap agreement are urged to test their supply chain savings under different values of τ.

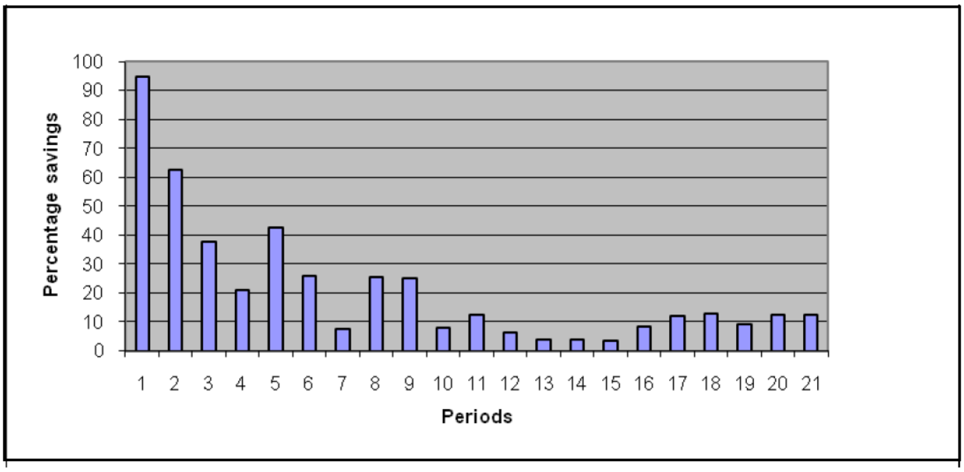

Figure 11. Cumulative Percentage Savings for Company A throughout the Entire Swap Period Before Sharing

3.3 Other Sensitivity Analysis Related Issues

When interested in swapping with competitors, companies might want to consider their gain/loss process throughout the swap period in addition to the overall supply chain savings. In scenario 5 of the base case, where demand is as given in the case, capacity is unconstrained, VO is unconstrained, τ is set to three periods, and the price is set constant at $450/MT, while both companies saved in the overall supply chain cost at the end of the two-year period, Company B did most of the work and was suffering more costs than Company A throughout the swap period. Figures 11 and 12, show how much more each company made throughout the swap period relative to the No-Swap scenario in order to achieve the desired savings.

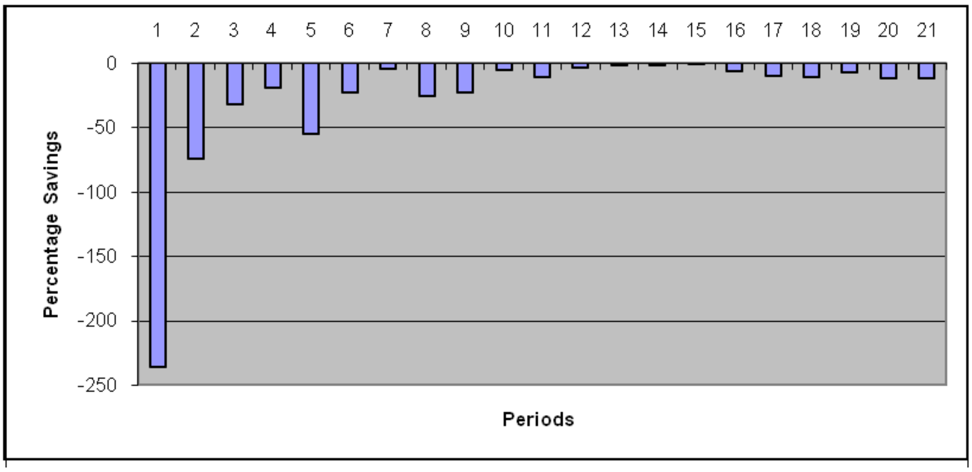

Figure 12. Cumulative Percentage Savings for Company B throughout the Entire Swap Period Before Sharing

If results of the base case, shown in Figures 11 and 12, is of concern to a company that is interested in undergoing a swap agreement with a competitor, then some restrictions should be enforced and agreed on in the swap contract. For example, restrictions on the VO between supply chain partners during a swap or on the production capacity availability for a swap can reduce the percentage of gain/loss for a company throughout the swap period. However, this comes with the expense of reducing the overall supply chain savings.

Figures 13 and 14 show the impact on both companies when applying constraints on the value of VO between supply chain partners, where demand pattern is as given in the case, capacity is set to be unconstrained, VO is set to 6000 MT only, τ is et to 3 periods, and the price pattern is set constant at $450/MT. While Company B has reduced its loss during the swap period (sharing a greater load with Company A), the overall supply chain saving has been reduced. In the scenario where the value of VO was unconstrained, the overall supply chain savings for each company was $902,198.94. On the other had, when the value of VO was constrained in order to share the load during the swap period, the overall supply chain savings per company came to $740,894.68. Accordingly, different swap strategies have different outcomes. Some offer great savings, but they come at the expense of a heavier workload, while others offer fewer savings and a lighter workload. Hence, the type of strategy to settle on remains the choice of companies interested in joining into a swap agreement.

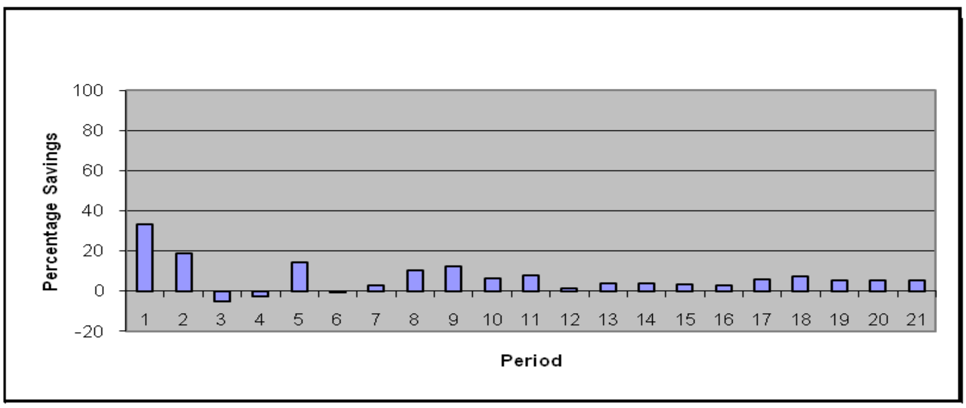

Figure 13. Cumulative Percentage Savings for Company A throughout the Entire Swap Period Before Sharing

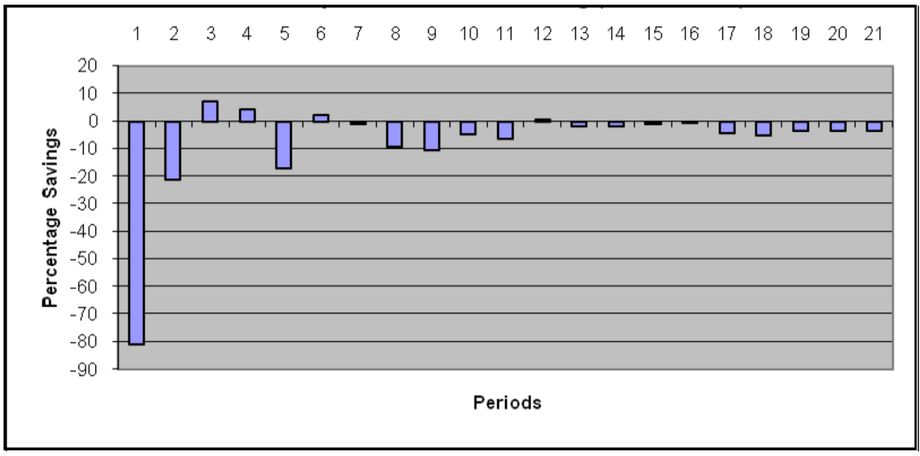

Figure 14. Cumulative Percentage Savings for Company B throughout the Entire Swap Period Before Sharing

4. Conclusion

The overriding purpose for this study was to perform a detailed sensitivity analysis of the swap problem to examine the effect of different operational parameters on the cost savings realized by parties involved in swap. Two companies from the petrochemical industry were chosen. These two companies (named company A and company B for anonymity) had been engaged in swapping their products for several years. A set of 432 different scenarios were developed by varying the values of demand pattern, capacity constraints, VO, sharing periodicity (τ), and price pattern. These scenarios were examined on swap practices of Companies A and B.

Results of the sensitivity analysis suggest that swapping in general can reduce supply chain costs. It was suggested that when swap decisions are made, the behavior of the parameters mentioned earlier (e.g., demand pattern, capacity constraints, VO, sharing periodicity) should be taken into consideration and various scenarios be evaluated to better determine *what, where, and how much to swap* in order to reduce supply chain (SC) costs. It was also shown that the interaction among these parameters can have a substantial impact on supply chain savings.

References

Al-Husain, R., Assavapokee, T., & Khumawala, B. (2008). Modeling the Supply Chain Swap Problem in the Petroleum Industry. *International Journal of Applied Decision Sciences*, *1*, 261-281. http://dx.doi.org/10.1504/IJADS.2008.021223

Anon (2002). Biofuel use promoted by European Parliament. *Lipid Technology*, *14*, 75. 2.

Belvardi, G., Kiraly, A., Varga, T., Gyozsan, Z., & Abonyi, J. (2012). Monte Carlo Simulation Based Performance Analysis of Supply Chains. *International Journals of Managing Value and Supply Chains*, *3*, 1-14. http://dx.doi.org/10.5121/ijmvsc.2012.3201

Eschenbach, T. G., & Gimpel, R. J. (1990). Stochastic sensitivity analysis, *The Engineering Economist*, *35*, 305-321. http://dx.doi.org/10.1080/00137919008903024

Eschenbach, T. G., & McKeague, L. S. (1989). Exposition on using graphs for sensitivity analysis. *The Engineering Economist*, *34*, 315-333. http://dx.doi.org/10.1080/00137918908902996

French, S. (1992). Mathematical programming approaches to sensitivity calculations in decision analysis. *Journal of the Operational Research Society*, *43*, 813-819. http://dx.doi.org/10.1057/jors.1992.120

Hussain, R., Assavapokee, T., & Khumawala, B. (2006). Supply Chain Management in the Petroleum Industry: Challenges and Opportunities. *International Journal of Global Logistics & Supply chain Management*, *1*, 90-97.

Khorramshahgol, R., Al-Hussain, R., & Tamiz, M. (2010). Application of Linear Programming to Swap Analysis in Supply Chain Management of Oil Industry. *Journal of Information and Optimization Sciences*, *31*, 1375-1388. http://dx.doi.org/10.1080/02522667.2010.10700033

Khorramshahgol, R., Tamiz, M., & Al-Hussain, R. (2014). Application of Goal Programming to Swap Analysis in Oil Industry. *Journal of Information and Optimization Sciences*, *35*, 73-91. http://dx.doi.org/10.1080/02522667.2014.894300

Kim, J., Realff, M., & Lee., J. (2011). Optimal Design and Global Sensitivity Analysis of Biomass Supply Chain

Networks for Biofuels under Uncertainty. *Computers and Chemical Engineering*, *35*, 1738-1751. http://dx.doi.org/10.1016/j.compchemeng.2011.02.008

Kleijnen, J. P. C. (1995) Sensitivity analysis and optimization of system dynamics models: regression analysis and statistical design of experiments. *System Dynamics Review*, *11*, 1-14. http://dx.doi.org/10.1002/sdr.4260110403

Li, C., Xiang, X., & Qu, Y. (2016). Product Quality Dynamics in Closed-Loop Supply Chains and its Sensitivity Analysis. *The Journal of Grey Systems*, *28*, 80-190.

Sahin, A., Yilmaz, A., & Atakan, C. (2008). An Investigation on the Shuttle Trade Dynamics of a Small-Open-Economy. *International Journal of Economic Sciences and Applied Research*, *1*, 1-12.

Umeda, S. (2014). Sensitivity Analysis of Reverse Supply Chain System Performance by using Simulation. *IFIP International Federation for information Processing*. B. Grabot (editor) 326-333. http://dx.doi.org/10.1007/978-3-662-44736-9_40

Zheng, Y., Liao, H., & Yang, X. (2016). Stochastic Pricing and Order Model with Transportation Mode Selection for Low-Carbon Retailers. *Sustainability, 8*, 14-23. http://dx.doi.org/10.3390/su8010048

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