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O.R. Applications

Tariff concessions in production sourcing

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Abstract

In this paper, we study a multi-stage production sourcing problem where tariff concessions can be exploited at the firm level using free trade agreements between countries. To solve the problem, an algorithm which embeds a very large-scale neighborhood (VSLN) search into a simulated annealing framework is developed. A numerical study is conducted to verify the effectiveness of the solution approach.

Keywords: Production sourcing; Tariffs; Heuristics

1. Introduction

There has been a proliferation of preferential and free trade agreements (FTAs) recently (Ju and Krishna, 1998) adding to those already in place – for example, the European Union (EU), the North American Free Trade Agreement (NAFTA), the Central European Free Trade Agreement (CEFTA), the Australia-United States Free Trade Agreement (AUS-FTA), the Japan and Singapore New Age Economic Partnership Agreement (JSEPA), and the China-ASEAN Free Trade Agreement (CAFTA). Many more continue to be shaped.

As firms evolve strategies to compete in international tariff concession environments, "tariff engineering" (Long, 2003) is beginning to play a larger role in regional and global manufacturing. Companies, such as Steve & Barry's (Lattman, 2005), have grown their businesses successfully by exploiting tariff agreements to lower costs. Global sourcing solutions providers, such as Li & Fung (Hong Kong), help customers take advantage of tariff preferences wherever possible (Magretta, 2002). The following is a simple illustration. To satisfy demand from Europe for apparel, Li & Fung procures yarn from a South Korea producer and has it woven and dyed in Taiwan. Zippers and buttons are purchased from Japanese companies located in China. All semi-finished components are then shipped to Thailand, where production is completed. In this example, other than a preferential trade agreement between South Korea and Taiwan, tariff concessions between China and Thailand (as part of ASEAN, the Association of Southeast Asian Nations), and Thailand (ASEAN) with the EU, impact outsourcing

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recommendations offered by Li & Fung. For more complex products, e.g., electronic toys, the number of manufacturing stages, which are dispersed regionally and globally, can escalate making outsourcing choices more difficult for the firm.

In this work, we develop a model which allows the firm to make sourcing and plant location decisions to take advantage of tariff concessions in a multi-country environment where FTAs come into play. We study how the firm can leverage its sourcing network using tariff concessions to lower production costs.

This paper is organized as follows. Section 2 provides a literature review. In Section 3, the problem is described and modeled as an integer program, which is shown to be NP-hard. In Section 4, a solution approach to the problem is provided using a multi-exchange heuristic embedded in simulated annealing. Numerical experimentation and an analysis of the results is given in Section 5, and the work concluded in Section 6.

2. Literature review

Trade agreements have been studied extensively from national, welfare and economic perspectives (Krueger, 2003; Mann, 2003; Chase, 2003) together with their impact at the macro level on industries (Krueger, 2003; Bair and Gereffi, 2003; Stordal, 2004). However, in the operations management literature there has been little work on the influence of trade agreements at the firm level. In Munson and Rosenblatt (1997), the authors study models where local content rules force firms to buy components from suppliers in a single country of manufacture. Here, the classical plant location model is extended to factor in local content requirements. Li et al. (in press) extended this by incorporating supplier capacity constraints. Kouvelis et al. (2004) provided a mixed integer programming model to design global networks, which incorporated government subsidies, trade tariffs and taxation issues. Their work focuses on special cases and provides useful insights and analysis.

In related operations management literature, early empirical work on international procurement is found in Davis et al. (1974), Monczka and Giunipero (1984), Vickery (1989), Carter and Narasimhan (1990), Min and Galle (1991) and Monczka and Trent (1991). The general supplier selection problem has been studied by Moore and Fearon (1973), Gaballa (1974), Bender et al. (1985), Kingsman (1986), Turner (1988), Chaudhry et al. (1993), Weber and Current (1993). Other studies on sourcing include Minner (2002), where inventory models in the global environment are provided, and Chung et al. (2004).

3. The *n*-stage *m*-country production line design problem

The problem we study can be described as a multi-stage production line design problem (PLD, in short) in which the firm makes decisions on where to outsource from and/or locate its manufacturing plants taking into account production costs as well as tariff concessions arising from FTAs. Assume that the firm produces a single product to sell in a market located in country D and that the product is manufactured in n stages where one or more stages can occur in any of m countries for which FTA concessions apply; see Fig. 1. Assume, for simplicity, that the firm incurs a fixed production cost for any stage in a given country. Depending on FTA tariff concessions available in its sourcing network located in these countries, the firm has to decide where each stage should be carried out to minimize the total production costs, including tariff costs.

In its prevalent form, an FTA between country i and j allows goods exported from country i into j to be tariff exempt if they originate in i, and vice versa. Tariff exemption or a lower tariff can be claimed if products satisfy rules of origin (ROO), and can qualify as originating from the exporting country i. ROO stipulate a local content rule, which requires that value added (local content) to the product in exporting country i must be no less than a specified percentage of its final total production value.

In order to calculate the value added as production moves from one stage to the next, costs are based on one unit of the product, where a "unit" is a generic term, and can mean a piece, carton etc. Denote the aggregate value of a unit of product up to stage k by V_k for $k = 1, \dots, n$, which includes all costs, including production and transportation costs, and the profit margin, up to stage k. Here, "production cost" is a collective term, and includes raw material cost, labor cost, local production tax, facility cost, factory rental cost, etc. In this model, production costs are taken as the price paid to an outsourced plant by the firm. V_k is commonly referred to as the "free on board" (FOB) price. In this case, FOB is determined by the firm and has a

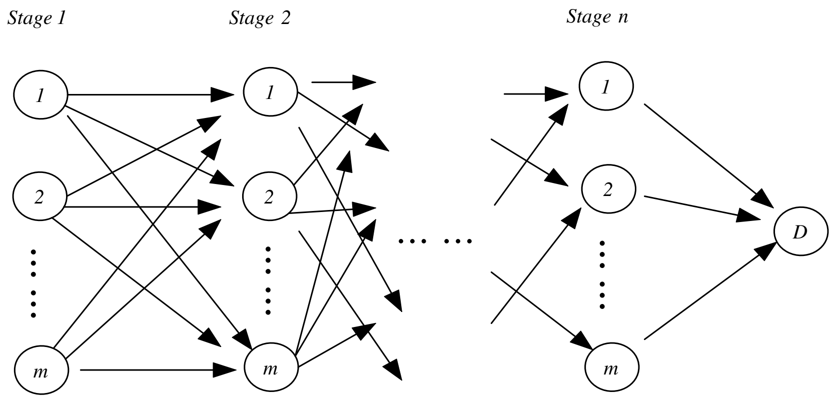

Fig. 1. The n-stage production line design problem.

fixed value, similar to the so-called "transfer price" in Vidal and Goetschalckx (2001), where products are transported in an internal network.

To calculate value added to a product in a particular country, we use the so-called "outward processing" method which is used in many FTAs (see e.g., the JSEPA: http://app.fta.gov.sg/asp/goods/guides.asp, the Singapore- Australian FTA: http://www.fta.gov.au), which takes value added as the cumulative value in a country for all stages of production. To be specific, let A_{ki} be the sum of the value added in country i up to stage k. If stage k occurs in country i and stage $k+1$ in country j, then the value added is used to calculate tariff as follows: if the value added in country i, A_{ki}, taken as a percentage of V_k, is less than a specified value β_{kij}, then tariff equal to α_{kij} (tariff rate) times the product value is incurred. Here, β_{kij} is a value added minimum threshold, i.e. the local content threshold, required for tariff elimination from country i to country j following production stage k. Both are specified in tariff rules in the applicable FTA. Otherwise, if the value added is higher than the threshold, the product is tariff free.

More formally, to describe the problem, the following parameters and decision variables are used:

- $m =$ the number of countries in production network
- $n =$ the number of production stages
- $t_{kij} =$ the unit transportation cost from country i to j, following stage k, where $k = 1, \ldots, n$; $i, j = 1, \ldots, m, m+1$, where $m+1 = D$ is the market country
- $P_{kj} =$ the production cost incurred in stage k in country j, i.e., price charged for stage k by the outsourced plant in country j, where $k = 1, \ldots, n;\ j = 1, \ldots, m$
- $I_{kj} = 1$ if stage k occurs in country j; 0 otherwise, for $k = 1, \ldots, n;\ j = 1, \ldots, m$
- $J_{kij} = 1$ if output of stage k is shipped from country i to country j; 0 otherwise, for $k = 1, \ldots, n;\ i, j = 1, \ldots, m$
- $T_{kij} =$ tariff paid to country j if stage k occurs in country i and stage $(k+1)$ occurs in country j, $i \neq j$; $T_{kii} = 0$, for $k = 1, \ldots, n$; $i, j = 1, \ldots, m+1$

We can now formulate the PLD as an integer program. In the program, the objective is to find an assignment of production stages to countries to minimize the total cost, including production and transportation costs, and tariff costs taking into consideration FTA tariff exemptions that apply between countries.

$$\min \sum_{k=1}^{n} \sum_{j=1}^{m} I_{kj} P_{kj} + \sum_{k=1}^{n-1} \sum_{i=1}^{m} \sum_{j=1}^{m} J_{kij} t_{kij} + \sum_{k=1}^{n-1} \sum_{i=1}^{m} \sum_{j=1}^{m} T_{kij} + \sum_{i=1}^{m} \left(t_{ni(m+1)} I_{ni} + T_{ni(m+1)} \right) \tag{1}$$

s.t.

$$\sum_{j=1}^{m} I_{kj} = 1, \quad k = 1, \ldots, n \tag{2}$$

$$I_{ki} = I_{k+1,j} = 1 \iff J_{kij} = 1 \iff J_{kij} + 1 \geqslant I_{ki} + I_{k+1,j}, \quad k = 1, \ldots, n-1; \quad i, j = 1, \ldots, m,\ i \neq j \tag{3}$$

$$\frac{\sum_{\kappa=1}^{k} I_{\kappa i} P_{\kappa i}}{V_k} < \beta_{kij} \& J_{kij} = 1 \Rightarrow T_{kij} = \alpha_{kij} V_k$$

$$\text{for } k = 1, \ldots, n, \quad i, j = 1, \ldots, m; \tag{4}$$

$$\Longleftrightarrow$$

$$h_{kij}.M \geqslant \beta_{kij} V_k - \sum_{\kappa=1}^{k} I_{\kappa i} P_{\alpha i}, \tag{5}$$

$$T_{kij} - \alpha_{kij} \cdot V_k \geqslant G \cdot (h_{kij} + J_{kij} - 2). \tag{6}$$

Eq. (2) ensure that each stage is assigned to exactly one country, while (3) ensure that I_{ki} and J_{kij} are consistent. Eq. (4) represent tariff threshold constraints, and (5) and (6) result from (4) by introducing binary variables $h_{kij} \in \{0, 1\}$ to transform the implication in (4) (Sierksma, 2002). Here, M is a suitably large number. In (6), G is a suitably large number, and both (5) and (6) hold for $k = 1, \ldots, n-1$, $i, j = 1, \ldots, m$ and if $k = n$, $j = m + 1$.

Before solving the problem, we show it to be NP-hard.

Theorem 1. *The PLD problem with a cumulative value add rule is NP-hard.*

Proof. NP-hardness is shown by reduction to the NP-hard 2-PARTITION problem (Garey and Johnson, 1979): Given an integer set $\{a_1, a_2, \ldots, a_n\}$ with $\sum_{i=1}^{n} a_i = 2M$, can we find a subset S with $\sum_{a_i \in S} a_i = M$?

An instance of PLD problem can be constructed as follows. Suppose only two countries are available, the production line consists of $(n + 2)$ stages, transportation costs is negligible and production costs are given as in Fig. 2.

From stages 1 to n in country 1, take these to be $a_1, a_2, \ldots, a_n$, and in country 2 take these to be 0 (negligible). Stage $(n + 1)$ can only occur in country 2 with production cost M and stage $(n + 2)$ can only occur in country 1 if we assume $M' \gg M$. The threshold value is specified as follows: it is zero between country 1 and 2 (i.e., there is no tariff between them), and 50% for final export from country 1 to the market D.

Suppose tariff imposed from country 1 to country D is high in the absence of tariff concession. The local value for the final product must be satisfied since final stage is carried out in country 1, which is at least 50% of the total value. We know stage $(n + 1)$ occurs in country 2 with value added M, so the value added in country 1 cannot be less than M, i.e., $V_{n+2} = 2M$ is the minimum possible cost. This requires that value added in country 1 from stages 1 to n to be exactly M. Hence, once the problem is solved, we know if a feasible solution to 2-PARTITION problem can be found, i.e., if the total cost is $2M$, then the answer is "yes"; otherwise it is "no". □

4. A multi-exchange heuristic embedded in simulated annealing

A solution approach for the PLD which uses a multi-exchange heuristic embedded in a simulated annealing algorithm can be developed. Here, the multi-exchange neighborhood local search is a variant of a very large-scale neighborhood (VLSN) search, which is suitable for this type of problem and motivated by Ahuja et al. (2002). The use of simulated annealing with an adapted VLSN search is new in two aspects: (1) neighborhoods are searched with a heuristic using a constructed estimated improvement graph, whereas in traditional VSLN search, exact improvement graphs are required (Ahuja et al., 2004), and (2) VLSN search is embedded into a simulated annealing metaheuristic framework.

Simulated annealing (SA) differs from standard hill-climbing search since it is able to accept downhill moves which can decrease the quality of the

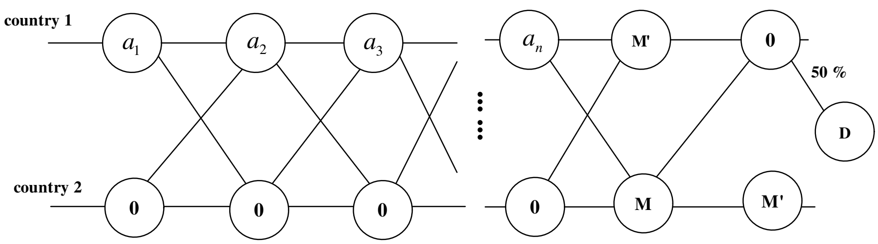

Fig. 2. 2-country multi-stage sequencing.

objective function with a probability related to a temperature variable (Dowsland, 1993). In Algorithm 1, the framework of the algorithm (called SAVSLN) which uses a SA framework with a multi-exchange heuristic is provided. In this algorithm, a geometric annealing scheme is used, with the constant C_0 taken to be 0.995, where a reheating mechanism is employed whenever

Algorithm 1. SAVLSN Framework

read input: n, m, V_k, t_{kij}, P_{kj}, α_{kij}, β_{kij}
$S \leftarrow$ *Weighted Probablistic Initial Solution Generation*
Temperature $\leftarrow T_{\max}$; *Iter* $\leftarrow 0$
while *Iter* $<$ *Max_Iter* and *Temperature* $>$ *T_Terminate* **do**
  with probability 0.5
    Stemp $\leftarrow$ *VLSN_Cycle*(S, *random*(2, $K_{\max}$))
  with probability 0.5
    Stemp $\leftarrow$ *VLSN_Path*(S, *random*(2, $K_{\max}$))
  $\delta = value(Stemp) - value(S)$
  if $\delta < 0$ **then**
    $S \leftarrow Stemp$
  else
    $p = e^{-\delta/Temperature}$
    with probability p
      $S \leftarrow Stemp$
    with probability $1 - p$
    reheat ()
  end if
  if $value(S) > best\_value$ **then**
    $best\_value \leftarrow value(S)$;
  end if
  $iter \leftarrow iter + 1$
  $Temperature \leftarrow Temperature * C_0$
end while

an iteration cannot yield a new current solution. This mechanism counters the effect of annealing to allow for a higher chance of diversifying local moves in later iterations. The reheating is geometrically defined by $Temperature = Temperature * \left(1 + \frac{(1-C_0)}{5}\right)$. From experiments, it was found that once reheating is used, solution quality can be improved by between 1% and 1.5%, on average.

4.1. Generating initial solutions

Let the array S of length n represent a solution where $S[i]$ is the index of country which stage i is assigned to, $1 \leqslant S[i] \leqslant m$, $1 \leqslant i \leqslant n$. Two methods were used to generate initial solutions. The first is to randomly choose a country for a stage to be processed in, which serves as a comparison for the second method. The second is to use a weighted probability to assign a country index to every stage, by considering the stages 1 to n sequentially. Since there is no tariff cost or transportation cost involved in stage 1 of production, the total cost of stage 1, if assigned to country j, $1 \leqslant j \leqslant m$, can be estimated to be the production cost P_{1j}. This is an estimation since the effect of assigning a country index to stage 1 on later decisions for stage 2 to stage n is not known. Define $Q_{1j} = \frac{1}{P_{1j}}$ and $Q_{\text{total}} = \sum_j Q_{1j}$ and assign j to stage 1 with probability $\frac{Q_{1j}}{Q_{\text{total}}}$. This is to increase the chance that stage 1 is processed in countries that have a smaller production cost. After stage 1 is assigned to a country, continue to decide country indices for stage 2 to n in a similar way, sequentially, except that the estimated cost for assigning country index j to stage k would, in addition, include transportation cost and tariff (if incurred) from the country where stage $(k-1)$ is processed. To decide a country index for the last stage, tariff and transportation cost to the destination is used.

4.2. Very large-scale neighborhood search

Given a solution $\mathbf{S}$, the neighborhood $\mathcal{N}(S)$ is defined as the set of all feasible solutions $\mathbf{S}'$ which are achievable from $\mathbf{S}$ by a single neighborhood move. In general, the larger the neighborhood size $|\mathcal{N}(\mathbf{S})|$ is, the better the solution quality will be after a local move. However, it is often the case that due to a very large number of neighborhood solutions, the running time for a neighborhood move is high. The idea of a VLSN search is based on maintaining a large set of neighborhood solutions while exploring these efficiently. For this, cyclic and path neighborhood exchange moves are used as the local moves.

4.2.1. Neighborhood structure

For a solution $\mathbf{S}$, define C_j, $1 \leqslant j \leqslant m$ by $C_j = \{i | S[i] = j,\ 1 \leqslant i \leqslant n\}$, which is the set of indexes of stages processed in country j. A cyclic exchange neighborhood move first selects K different countries $i_1, i_2, \ldots, i_K$ such that $C_{i_j} \neq \emptyset$, for $j \in \{1, 2, \ldots, K\}$. In each selected country j, choose stage $t_j \in C_{i_j}$ and reassign stages t_1 to t_K to country $C_{i_j}, j = 1, \ldots, K$ in a cyclic manner: $S[t_i] := S[t_{i+1}]$ for $i = 1, \ldots, K-1$, and $S[t_K] := S[t_1]$. Consequently, C_j; $1 \leqslant j \leqslant m$ is changed accordingly and the changes take place simultaneously. For the

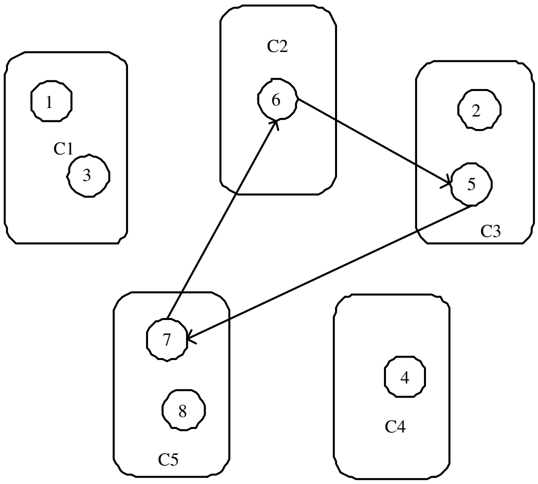

Fig. 3. Example of a VLSN search cyclic exchange with $n = 8$, $m = 5$, $K = 3$.

simple example illustrated in Fig. 3, after the local move, the three sets C_2, C_3 and C_5 are changed to $C_2 = \{7\}$, $C_3 = \{2, 6\}$, $C_5 = \{5, 8\}$, while C_1 and C_4 remain unchanged. It is clear that by the Kth-cyclic change, the number of neighborhood solutions is $(n/K)^K K!$ assuming the n stages are uniformly allocated in m countries, and in general, the number of neighborhood solutions $\mathcal{N}(\mathbf{S}) = \Omega(n^K)$. When K is allowed to vary linearly with n, the neighborhood size increases exponentially with n. In the algorithm developed here, $K_{\max}$ is fixed to be approximately 10% as large as n, and in each iteration of a cyclic local move, K is selected randomly in the range $[2, K_{\max}]$. A neighborhood in path exchange is very similar to a cyclic one although path exchange does not select any stage in C_{i_K} to move to C_{i_1}.

In order to choose K proper stages, the estimated total cost change must be specified when stages are chosen in the local move. The notion of an improvement graph (Ahuja et al., 2004) can be used for this. The estimated improvement graph developed here differs from that used in Ahuja et al. (2004) where the arc weights actually reflect the exact cost change of stages. Since cost calculations in the PLD problem are impossible with only partial information, arc weights in the improvement graph can only be estimates. This is discussed in the next section.

4.2.2. Estimated improvement graph

Given a solution $\mathbf{S}$ and C_j, $1 \leqslant j \leqslant m$ denned in the previous section, an *estimated improvement graph* is a directed graph $G(\mathbf{S}) = (V, E)$ in which the set of vertices V contains n nodes: v_q, $q = 1, \ldots, n$ each representing a stage q in the solution $\mathbf{S}$. The arc set E represents the relationship between different stages, where there is a directed arc (q, l) from v_q to v_l if and only if $S[q] \neq S[l]$. The weight of each arc (p, l) is taken to be E_{pl} where:

$$E_{ql} = \begin{cases} P_{q,S[l]} - P_{l,S[l]}, & \text{if } q = 1 \text{ or } l = 1 \\ P_{q,S[l]} - P_{l,S[l]} + t_{q,Sq-1,Sl} & \\ -t_{l,S[l-l],S[l]} + T_{q,S[q-l],S[l]} - T_{l,S[l-l],S[l]}, & \text{Otherwise} \end{cases}$$

This weight is designed to reflect the total cost change if stage q is reassigned to country $S[l]$ and stage l reassigned to some other country. The above function E_{kl} can only be an estimation because the exact transportation cost and tariff cost for stage q in country $S[j]$ are not available until all stages $1, \ldots, q-1$ are fixed. However, these $q-1$ stages may be used in the current cyclic/path exchange, and therefore cannot be fixed yet.

4.2.3. Probabilistic selection of cycles and paths

Once the estimated improvement graph has been constructed, the algorithm first randomly chooses K countries C_{i_j}, $j = 1, 2, \ldots, K$. If it is a cyclic neighborhood move, $C_{i_j} \neq 0$, while for a path exchange, $C_{i_K} = \emptyset$ is possible. In the neighborhood search, a stage in C_{i1} is chosen to be included as the first stage in the cycle/path as follows: Let the production cost P_{ji_1} be the indicator of the preference to choose stage j originally in C_{i_1} for all j such that $j \in C_{i_1}$. Define $P_{\text{total}} = \sum_j P_{ji_1}$. Then stage $j \in C_{i_1}$ is selected by the cyclic neighborhood change with probability $\frac{P_{ji_1}}{P_{\text{total}}}$. This procedure is similar to when the country index is generated for the first stage in the weighted probability initial solution generation described in section 3.1. However, there are two differences. The first is the fact that since we are selecting stages to "move away" from the currently assigned countries, assigning a larger probability to stages that have a large production costs rather than those which have a small production costs is preferred. The second is that probabilities are used to select a stage when the country index C_{i_1} is fixed, unlike in initial solution generation when the stage is fixed and the country index is selected.

When a stage from country C_{i_1} is selected, one stage for each of the remaining $K-1$ countries is selected sequentially to be used in the cyclic exchange move. Let the index of the selected stage from country C_{i_j} be l_j for $j = 1, 2, \ldots, K$. The selection of l_j is based on the value of l_{j-1} for $2 \leqslant j \leqslant K$. In the estimated improvement graph, there should be an arc from the node representing l_{j-1} to every node in C_{i_j} by definition. A negative arc weight indicates a potential improvement in solution quality if the exchange local move is made to contain the stages associated with this arc. Arc weights are modified in the following way: first, multiply these by -1 and then add a minimum positive number to the arcs to make all weights positive. For example, weights $\{1, 2, 3, -4, -5\}$ are changed to $\{-1, -2, -3, 4, 5\}$ and then to $\{3, 2, 1, 8, 9\}$. This is to facilitate later calculations of probabilities used for selecting each stage in C_{i_j}. Let E'_{pq} be the modified arc weight from stage p to stage q and $Arc_{\text{total}} = \sum_{q \in C_{i_j}} E'_{l_{i-1}q}$ and then select stage $q \in C_{i_j}$ in the cyclic exchange neighborhood move with probability $E'_{l_{i-1}q}/Arc_{\text{total}}$. If there is a cyclic exchange, the cost from C_{i_K} to C_{i_1} is included using the arc weight E_{ql_1} to determine the probability of selecting the stage $q \in C_{i_K}$. If the local move is a path exchange, it is not necessary to select a stage from C_{i_K}. When l_i for $i \in \{1, 2, \ldots, K\}$ are fixed, a cyclic/path exchange is performed to complete an iteration of the neighborhood search.

5. Numerical experiments

5.1. Test instances generation

As the problem is new, no benchmark test sets have been established. In order to determine the effectiveness of the solution approach, test instances were generated to represent realistic situations as far as possible. These include using the following attributes for the test instances:

- Product value increases as more stages are completed. Specify the following parameters: S_i is the base product value for the ith one third stages, $i = 1, 2, 3$; inc_i, the exponential increment of product value compared with the value in the previous stage; and d_i and u_i, is the variance in product value. For stages 1 to $\lfloor n/3 \rfloor$ which belong to the first one third stages, the FOB values of output of stage j are defined by:

  $$V_j = S_1 * (1 + inc_1)^{(j-1)} \times \mathsf{Unif}[1 - d_1, 1 + u_1], \quad \text{for } j \in \{1, 2, \ldots, \lfloor n/3 \rfloor\},$$

  where $\mathsf{Unif}[x, y]$ generates a real number uniformly in $[x, y]$. The FOB values for the remaining stages are calculated in the same way with the respective parameters.
- Some countries have a relatively lower production cost (e.g., for labor intensive work in Asia) for some stages of production. This is addressed by introducing parameters d_{ij} and u_{ij}, where $i \in \{1, \ldots, n\}$ and $j \in \{1, \ldots, m\}$, which specify how much change the production cost of stage i in country j can have compared with V_i.

  $$P_{ij} = V_i \times \mathsf{Unif}[1 - d_{ij}, 1 + u_{ij}], \quad \text{for } i \in \{1, \ldots, n\}, j \in \{1, \ldots, m\}.$$

  The $n \times m$ matrices $\mathbf{d} = [d_{ij}]$ and $\mathbf{u} = [u_{ij}]$ are assigned values to represent country preferences for different stages. For example, if country j is preferred in the first third of the stages, higher d_{ij} and lower u_{ij} values can be used for stages 1 to $[n/3]$.
- The transportation cost t_{kij} is taken to be proportional to the product of the distance between points and the value V_i, with a 10% variance limit.
- Tariff rates and value add threshold values are specified by the parameters *tar* and *lcr* which range between 20% and 50% in value. Both are subject to a 40% variation limit.

5.2. Experiments on the parameter K_{max}

In order to evaluate the performance of the SAVLSN algorithm, we investigated the effect of the most important parameter of the VLSN local search method, i.e., $K_{\max}$, on performance and compared the SAVLSN algorithm between $K_{\max} = 0.1n$ and $K_{\max} = 0.5n$. Since there are no established benchmarks, 5 groups of test sets were generated using different scales. Each test set group consists of 20 test instances generated according to the categories described in the previous section. To ascertain the effectiveness of the VLSN search used in the simulated annealing framework, the acceptance rate of the local move in the framework for different iteration ranges was compared. All the experiments were conducted on P4, 1.4 GHz CPU with 256 Mb of memory.

The experimental results are provided in Table 1, where $\mu_{\text{SA}_{0.1}}$ and $\mu_{\text{SA}_{0.5}}$ is the average costs obtained by the SAVLSN algorithm using $0.1n$ and $0.5n$ for $K_{\max}$, respectively; σ_{SA} measures the standard deviation of the results for the 20 test instances in each group, and t_1 and t_2 is the average running time in

Table 1
Comparing $\mathrm{SAVLSN}_{0.1}$ and $\mathrm{SAVLSN}_{0.5}$

n	m	$\mu_{\mathrm{SA}_{0.1}}$	$\sigma_{0.1}$	t_1	$\mu_{\mathrm{SA}_{0.5}}$	$\sigma_{0.5}$	t_2	δ (%)
60	30	8.02	0.34	1.21	8.13	0.35	3.16	1.37
80	30	114.04	5.86	1.25	117.55	7.85	4.29	3.04
100	50	1740.83	48.61	2.25	1840.11	78.05	5.85	5.70
100	80	1765.77	82.17	2.49	1924.26	90.09	22.34	8.98
120	50	2489.85	698.92	14.39	27446.21	1147.35	35.11	10.23

seconds for each instance; δ measures the difference between solutions of $\mathrm{SAVLSN}_{0.1}$ over $\mathrm{SAVLSN}_{0.5}$, as a percentage. From the table, it can be seen that setting $K_{\max} = 0.1n$ provides 1% to 10% better results compared with $K_{\max} = 0.5n$. This results from the fact that a large estimated cycle length will easily lose the advantage for small adjustments. In addition, the standard deviation of the results was higher than those for $\mathrm{SAVLSN}_{0.1}$. Both parameter settings result in fast running times of less than 40 seconds, where the $\mathrm{SAVLSN}_{0.1}$ algorithm obtains results within 15 seconds. The longer running time for $\mathrm{SAVLSN}_{0.5}$ is expected in view of the longer cycle local search. From the experiments, for different problems, setting $K_{\max}$ to equal $0.1n$ was found to be a good choice.

To further analyze the use of simulated annealing for the $\mathrm{SAVLSN}_{0.1}$ and $\mathrm{SAVLSN}_{0.5}$ algorithms, we recorded the acceptance rate of the VLSN local move in simulated annealing framework for iterations ranging from 1 to 1000 without reheating since this affects the natural acceptance rate of the algorithm. The acceptance rate was recorded for every 100 iterations performed. The results for the 20 test instances for $n = 100$ and $m = 50$ can be found in Fig. 4. Each point with x-axis value i represents the acceptance rate for iteration $100(i-1)$ to $100i$. Other groups of test instances had similar acceptance rates. The initial acceptance rate for simulated annealing should ideally be approximately 60% (Michalewicz and Fogel, 2000), which explains why $\mathrm{SAVLSN}_{0.1}$ with an initial acceptance rate near to 65% performed better than $\mathrm{SAVLSN}_{0.5}$ which had an acceptance rate of about 28%.

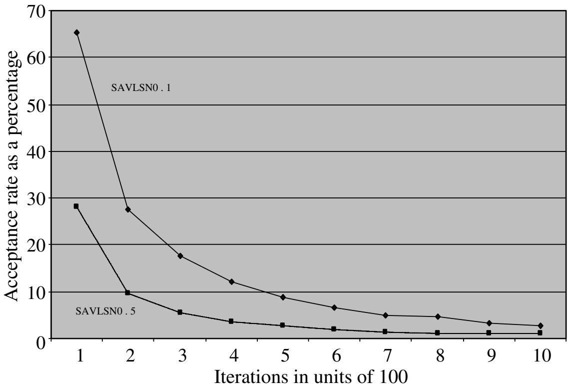

Fig. 4. Acceptance rate for the first 1000 iterations.

5.3. Comparing initial solution generation

A weighted probability method was used to generate the initial solution, which was compared with a random generation method. Instances with $n = 80$ and $m = 30$ were used to compare performance, and all parameters were assigned the same values. These recorded close running times of 19.23 and 17.38 seconds, for the weighted and random probability method, respectively. The results using the weighted probability method were 11.3% better than those from the random method. Although solution quality can be improved by multi-restarts, each requiring only a few seconds, the focus is on solution convergence; hence, an initial solution was fixed in each run. Experimental results are presented in Fig. 5.

The x-axis represents the running time consumed by each method at that point, and the y-axis gives the difference of the current solution to the best

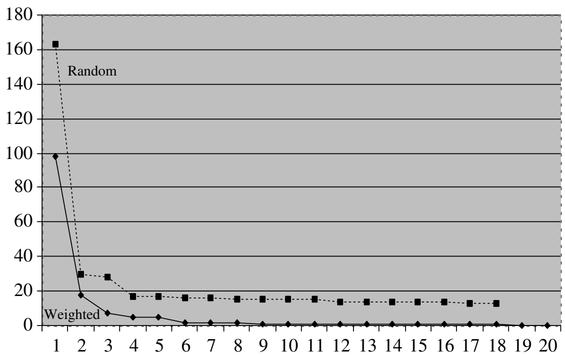

Fig. 5. Convergence of initial solution generation methods.

solution obtained by the weighted probability method, as a percentage. The value at $x = 0$ is the initial solution. It is not surprising that a weighted probability led to better starting solutions since this method takes the various costs into consideration. Both methods converge very quickly, to within 10% of the final value within 3 seconds. From this, we conclude that the weighted probability method provides better performance in both solution quality and convergence rate.

5.4. CPLEX and the SAVLSN

Comparisons were made between the SAVLSN and ILOG CPLEX 9.0. Here, $K_{\max}$ for the SAVLSN algorithm is taken to be $0.1n$. From the experiments, it was determined that even when both m and n are of moderate size – 40 to 60 –, CPLEX was not able to obtain a feasible solution within arbitrary time and terminated with an "out of memory" error. Hence, for comparisons, test instances were limited to the largest range for which CPLEX was able to obtain feasible solutions. Two groups of small test instances were generated, each with 21 test cases starting from $n = 5$, $m = 5$, and increasing to $n = 30$ and $m = 30$. A time limit 10,000 seconds was set for CPLEX, and if after this time an optimal solution was not found, the best solution obtained is reported. Instances in the first group had a fixed tariff rate of 30% and value added threshold of 30%, both with up to 20% variation, while instances of the second group had a tariff rate 50% and value added threshold of 50%, both with up to 20% variation. The results for the first 21 instances is provided in Table 2, where t_1 and t_2 is the time used by CPLEX and SAVLSN, respectively. If CPLEX did not complete within 10,000 seconds, the t_1 column shows a hyphen -; the lower bound obtained by CPLEX at 10,000 seconds is presented in the "LB" column. Ratio_1 is the ratio of solution value from the SAVLSN algorithm over the solution from CPLEX, and Ratio2 is the ratio of the solution from the SAVLSN algorithm over LB.

Among these instances, 9 (42.9%) were optimal; 3 (14.3%) were better than CPLEX solutions by a percentage of 0.3–7%, obtained within 10,000 seconds; 6 (28.6%) were within 1% of CPLEX's solutions, and only three instances were worse than CPLEX's results by 1–5%. Nevertheless, CPLEX obtained 15 optimal results out of the 21 instances. For instances where optimal solutions were not obtained, SAVLSN was always within 10% of the lower bound. The SAVLSN algorithm was more stable providing the solutions within 10–25 seconds, while CPLEX's time requirement was approximately exponential to the size of instance. For the 9 instances where CPLEX gave better results by 0.11–4.08%, CPLEX used 8–545 times the running time required by the

Table 2
Experimental results for instances with a 30% tariff and value add threshold

Size	CPLEX	t_1	LB	SAVLSN	t_2	Ratio_1 (%)	Ratio_2 (%)
5_5	224.772	1.00	–	224.772	10.98	100.00	–
10_5	440.257	1.00	–	440.257	26.21	100.00	–
10_10	455.606	6.00	–	455.606	19.93	100.00	–
15_5	692.283	1.00	–	693.864	15.15	100.23	–
15_10	711.747	6.00	–	711.747	14.89	100.00	–
15_15	580.890	17.00	–	580.890	16.22	100.00	–
20_5	1481.703	1.00	–	1481.703	17.89	100.00	–
20_10	1527.546	105.00	–	1527.546	16.55	100.00	–
20_15	1394.503	461.00	–	1394.503	17.48	100.00	–
20_20	1078.740	1353.00	–	1122.738	17.48	104.08	–
25_5	2000.440	1.00	–	2003.950	21.74	100.18	–
25_10	2203.780	157.00	–	2206.119	20.35	100.11	–
25_15	1768.260	1345.00	–	1822.545	19.96	103.07	–
25_20	1686.560	–	1683.990	1726.465	18.36	102.37	102.52
25_25	1800.390	–	1699.850	1794.241	19.12	99.66	105.55
30_5	2577.530	5.00	–	2577.534	23.40	100.00	–
30_10	2620.060	599.00	–	2631.067	23.52	100.42	–
30_15	2229.780	6936.00	–	2247.729	22.30	100.80	–
30_20	2474.420	–	2301.620	2477.636	21.34	100.13	107.65
30_25	2652.290	–	2394.690	2600.158	21.61	98.03	108.58
30_30	2423.700	–	2117.080	2258.655	22.60	93.19	106.69

SAVLSN algorithm. In addition, considering the heuristic nature of the SAVLSN algorithm and the fact that we limited the instance size when using CPLEX, we can say that the SAVLSN algorithm has an advantage over CPLEX.

The results of the second group of experiments are given in Table 3. For this group, for two instances (25_15, 30_20), the the SAVLSN algorithm's results were more than 5% worse than those from CPLEX. This can be explained by the fact that the SAVLSN algorithm uses a cyclic/path exchange local move, and although the path exchange local move can possibly decrease the number of countries involved in the n stages of production, the cyclic exchange move never decreases this number. This is a disadvantage of the SAVLSN algorithm, which is not as efficient as CPLEX in exploring search regions with a very small number of countries when compared with the number of stages.

However, CPLEX failed to generate satisfactory solutions for instances with slightly larger size. In the experiments, three additional instances (40_40, 50_50 and 60_60) were used with tariff rate and value added threshold both fixed at 30%. CPLEX was allowed to run for 10,000 seconds for both the first two instances without providing optimal solutions. For the 60_60 test instance, CPLEX was not able to find a feasible solution while the SAVLSN algorithm obtained a solution within 70 seconds. For the 40_40 instance CPLEX's solution was 4.6% worse than that from the SAVLSN algorithm, obtained in 40 seconds; for the 50_50 instance CPLEX's solution was 22.8% worse than the solution from the SAVLSN algorithm, obtained in 48 seconds. Moreover, there was a 27% and 32% difference between CPLEX's solution and the lower bound for the 40_40 and 50_50 instances, respectively. The SAVLSN algorithm was able to handle larger test instances more efficiently than CPLEX, and is better suited for problems with a large number of stages.

To compare the speed of the SAVLSN algorithm and CPLEX, an important factor in practical implementation, the SAVLSN algorithm solutions were found following which solutions were obtained by CPLEX which were no worse than those from the SAVLSN algorithm, and the time consumed by CPLEX recorded. The results are presented in Tables 4 and 5 for the cases with tariff rate and value added both equal to 30% and both equal to 50%. *Ratio* is the time required by CPLEX divided by time used by the SAVLSN algorithm. The tables do not include cases where both methods obtained optimal solutions; here time performance can be directly compared from Tables 2 and 3. From the two tables we see that, to achieve the same performance as the SAVLSN algorithm, CPLEX required significantly more time, ranging from several times

Table 3
Experimental results for instances with a 50% tariff and value-add threshold

Size	CPLEX	t_1	LB	SAVLSN	t_2	Ratio_1 (%)	Ratio_2 (%)
5_5	293.538	1.00	–	293.538	37.99	100.00	–
10_5	402.631	1.00	–	402.631	24.11	100.00	–
10_10	424.003	3.00	–	424.003	24.48	100.00	–
15_5	770.252	1.00	–	770.252	30.87	100.00	–
15_10	749.333	63.00	–	749.333	55.62	100.00	–
15_15	629.977	47.00	–	629.977	28.77	100.00	–
20_5	1291.777	2.00	–	1291.777	35.06	100.00	–
20_10	1282.450	14.00	–	1295.130	34.32	100.99	–
20_15	1323.949	299.00	–	1323.949	34.16	100.00	–
20_20	1287.680	1947.00	–	1308.052	33.51	101.58	–
25_5	2149.300	4.00	–	2200.713	39.16	102.39	–
25_10	1957.030	407.00	–	1963.642	38.31	100.34	–
25_15	1886.950	744.00	–	2041.687	37.58	108.20	–
25_20	1850.320	4807.00	–	1890.099	45.74	102.15	–
25_25	1729.000	–	1698.430	1800.747	43.82	104.15	106.02
30_5	2542.350	14.00	–	2547.072	42.63	100.19	–
30_10	2856.920	1163.00	–	2871.363	44.22	100.51	–
30_15	2430.150	–	2353.270	2440.994	44.62	100.45	103.73
30_20	2288.420	–	2144.240	2452.440	42.01	107.17	114.37
30_25	2465.600	–	2218.340	2518.320	41.62	102.14	113.52
30_30	2618.950	–	2346.150	2573.357	45.27	98.26	109.68

Table 4
Time comparisons with tariff rate and value-added threshold equal 30%

Size	CPLEX time	SAVLSN time	Ratio
20_20	491	17.48	28.9
25_5	2	21.74	0.09
25_10	124	20.35	6.09
25_15	30	19.96	1.50
25_20	182	18.36	9.91
25_25	12718	19.12	665.17
30_10	507	23.52	21.56
30_15	4619	22.30	207.13
30_20	8935	21.34	418.70
30_25	38855[a]	21.61	1798
30_30	44104[a]	22.60	1951

[a] CPLEX ran out of memory at the time result was recorded.

Table 5
Time comparisons with tariff rate and value-added threshold equal 50%

Size	CPLEX time	SAVLSN time	Ratio
20_10	10	34.32	0.29
20_20	108	33.51	3.22
25_5	2	39.16	0.05
25_10	370	38.31	9.66
25_15	38	37.58	1.01
25_20	1013	45.74	22.15
25_25	1498	43.82	34.18
30_5	11	42.63	0.26
30_10	597	44.22	13.50
30_15	6730	44.62	150.83
30_20	95	42.01	2.26
30_25	351	41.62	8.43
30_30	39364.19[a]	45.27	869.54

[a] CPLEX ran out of memory at the time result was recorded.

to hundreds of times more. The only exceptions were when the instance sizes are small, in which case a branch-and-cut exact method such as CPLEX is expected outperform a heuristic.

5.5. Comparison with greedy heuristics

Having examined the efficiency of the algorithm against CPLEX, we examined how tariff concessions can benefit companies which are able to exploit it, and how much the heuristic approach to the problem can reduce costs when compared with intuitive and widely-used greedy production strategies. In particular, we consider the following intuitive greedy strategies adopted in practice (Long, 2003):

- *Material Oriented Strategy* (MATS): Choose the country for a particular production stage with the smallest production cost.
- *Market Oriented Strategy* (MORS): Choose production locations nearest to the market and process all stages in this country.

To better understand the impact of tariff concessions on planning decisions, we compared the performance of the SAVLSN method with tariff benefits (SALVSN), the SAVLSN without tariff benefits (SAVLSN w/o FTA), and the greedy MATS and MORS approaches.

Experimental results are presented in Fig. 6. The *x*-axis represents the size of the test instances in the form of *n_m*, where *n* and *m* represent the number of stages and number of countries, respectively. All test instances use a fixed 30% tariff rate and 30% value added threshold, with a 20% variation limit. The *y*-axis represents the best total cost obtained. From the figure, the SAVLSN algorithm with tariff benefits results in the least cost when

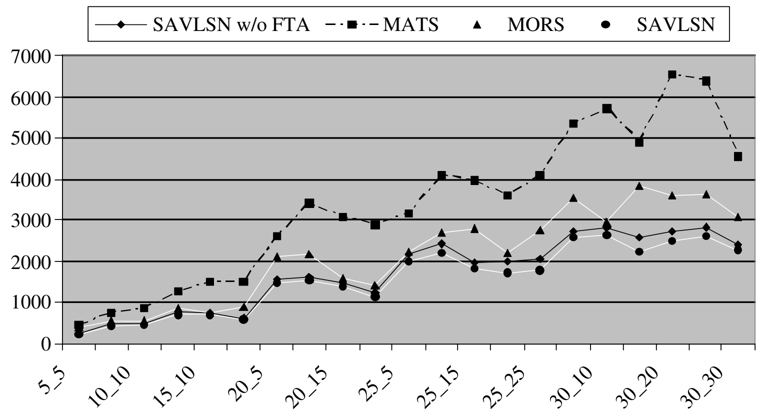

Fig. 6. Comparisons with greedy approaches.

compared with the other approaches. The gap between the SAVLSN algorithm and MORS approach varies from 20% to 50% as test sizes increase. Moreover, the difference between the MATS approach and the SAVLSN algorithm can be as much as 100% for large instances. SAVLSN performs better than the greedy algorithms. As instance size increases, the advantage from tariff concessions increases since the larger number of stages and countries allow for greater choice. The SAVLSN using tariff concessions provided a 10% cost reduction when compared with the SAVLSN without concessions.

6. Summary

In this paper, we studied a multi-stage production sourcing problem where free trade tariff concessions can be exploited to lower costs. The model developed is new, and adds to the existing - but sparse - literature in operations management. It can be used at the firm level to design a supply chain which spans a number of countries where free trade agreements come into play. To solve the problem, we used a multi-exchange heuristic which employs a VSLN search based on an estimated improvement graph. This method of embedding a VSLN neighborhood search in a simulated annealing framework is new and is shown to be effective in the numerical study conducted. In particular, the multi-exchange heuristic was found to be superior in speed to a commercially-available solver, and is able to provide solutions for larger, more realistic problem sizes.

Although simplifying assumptions are made in this work, the longer term goal would be to optimize the firm's sourcing when a larger range of implications of FTAs is included. For example, when the effect of different FTAs which govern different groups of countries which overlap is factored into the sourcing problem.

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