A robustness approach to international sourcing

Genaro J. Gutierrez
Management Department, University of Texas at Austin, Austin, TX 78712, USA

and

Panagiotis Kouvelis
Fuqua School of Business, Duke University, Durham, NC 27708-0120, USA

An important advantage of the use of international sourcing networks (i.e. selection of suppliers in various countries to support the demands of the firm's international factory network) is the resulting hedging power against real exchange rate changes in the international environment. Due to the uncertainty of future real exchange rate changes, the international manager wants to develop a sourcing network that is relatively insensitive (i.e. robust) to the potential changes of the macroeconomic parameters over a planning horizon. In our paper, we formally develop a *robust approach to international sourcing*. This approach develops the international supplier network in a way that adequately hedges the firm's performance against the worst contingency in terms of realizable real exchange rate shocks over a planning horizon. We present an algorithm to obtain the N best robust solutions (i.e. sourcing networks) to the international sourcing problem. Some computational results on the effectiveness of the approach are provided. We also demonstrate how the approach can be used to evaluate various sourcing strategies.

1. Introduction

The last twenty years have witnessed the evolution of a new global manufacturing environment. Previously, the international market was the preserve of large multinational corporations and generally was ignored by domestic firms. Today, it is essential that virtually all manufacturers be aware of and participate in international markets. Faced with intense global competition, firms are turning to international (global) sourcing as a competitive strategy. The main reasons for international sourcing are lower costs, improved quality, operational flexibility and access to new technology. To maintain a global competitive advantage, firms are maintaining international factory networks and a large peripheral network of suppliers for these factories. For references with extensive discussion of such international manufacturing configurations, see Ferdows [9], Oliff et al. [28], Cohen et al. [2], Flaherty [10], Huchzermeier and Cohen [16], Kogut and Kulatilaka [22], and McGrath and Hoole [25]. One of the most challenging managerial tasks for international manufacturing environments is the development of the *international supplier network* (also referred to as a *sourcing network*), i.e. the selection of a set of suppliers for the factory network, to enhance the operational flexibility and cost efficiency of the firm's international manufacturing activities. Our paper addresses this problem and suggests a managerially attractive, and computationally effective, approach for its solution.

The cost, quality and access to technology aspects of international sourcing are usually well understood. However, the importance of the available operational flexibility in such networks and the resulting hedging power against exchange rate changes in the international environment are not as well understood. We briefly discuss them below for the purpose of introducing the international sourcing problem. For an extensive discussion of the issue, see Kogut [21], Kogut and Kulatilaka [22], Huchzermeier [17], and Huchzermeier and Cohen [16]. For a detailed economic reference on effects of exchange rates on manufacturing firms, see Hooper and Mann [15].

A common problem facing global corporations is hedging against fluctuations of exchange rates that may give cost advantage to local producers or to manufacturers sourcing in certain regions of the world (see examples of such practices in Lessard and Lightstone [24], Kogut [21], and Huchzermeier [17]). Over the long term, the exchange rate for the currency of two countries should be such that a monetary unit of a country has the same purchasing power in both countries. This is formally expressed by economists in the Purchasing Power Parity (PPP) concept. PPP implies that the rate of nominal change of an exchange rate should be equal to the difference between inflation rates for the two currencies. However, empirical evidence indicates that PPP is not a good explanation of exchange rate movements, except in the very long run. In the short or medium time intervals, deviations from PPP predictions lead to *real* change of exchange rates (i.e. one that changes the relative prices of the goods produced by firms) and can create significant advantages/disadvantages for firms operating in the global arena. To illustrate this point, in figure 1 we present a comparison of the price indices of five countries. Using the exchange rate and wholesale price indices reported in Dalby and Flaherty [4], we plotted the equivalent wholesale price indices of five different countries in U.S. dollars over a period of time. As we observe, the plotted lines do not overlap perfectly with each other, as would have been the case if exchange rate fluctuations reflected accurately local price changes (i.e. inflation). Instead, the lines criss-cross each other several times, thus giving the local producers of some countries temporary cost advantages. To better illustrate this point, in figure 2 we computed the ratio of the exchange rate adjusted price index of each country with respect to the price index in the U.S. as a basis of comparison. The wholesale price index of the U.S. is represented as a horizontal line (at 1), and is used as a point of reference. As an example to demonstrate our point, we can observe from figure 2 that a producer located in France enjoys a cost advantage over a producer located in the U.S. in the period 1970–72, but is at a disadvantage during 1973–75.

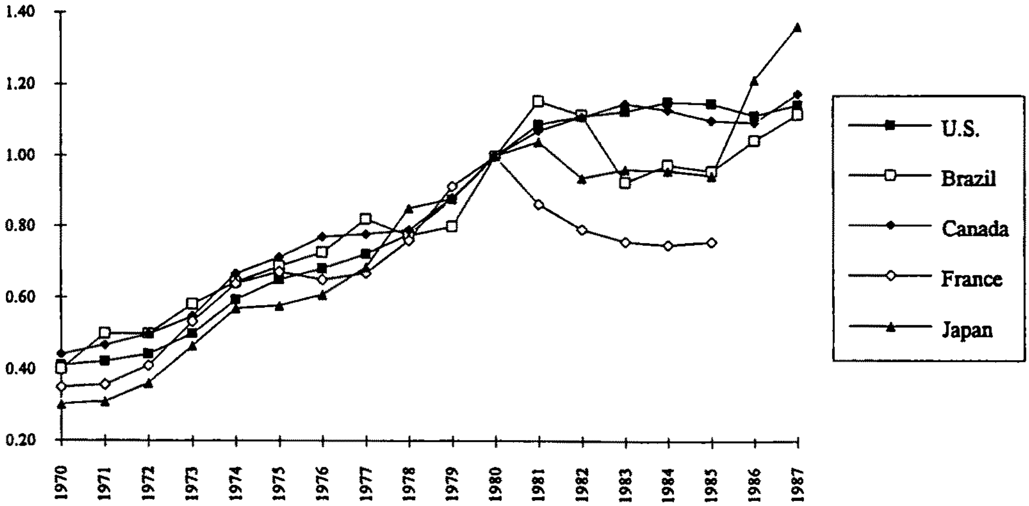

Figure 1. Wholesale price indices in U.S. dollars (base: 1980 = 1.0).

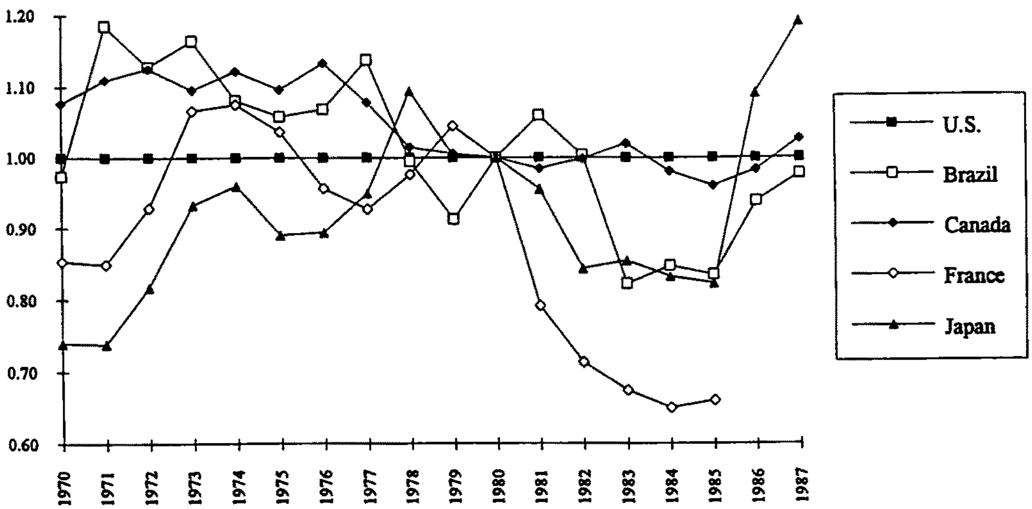

Figure 2. Price indices relative to the price index of the U.S. (base: price index of the U.S. = 1.0).

It is apparent from the above discussion that in the short term a firm that maintains an international supplier network can exploit the real exchange rate changes in lowering its production costs by shifting production orders to suppliers located in countries favored by the current exchange rate. The exercise of such an option involves evaluation of the following tradeoffs: loss of economies of scale, production cost savings, additional transportation costs, and cost of maintaining a rather large active set of suppliers. However, evaluation of these tradeoffs becomes a complicated task due to the future uncertainty of real exchange rate changes (i.e. uncertainties of both nominal exchange rates and inflation rates) and the subsequent uncertainty of sourcing costs from suppliers. In an era of Just-In-Time (JIT) manufacturing, quality and time based competition, working relationships with suppliers have to be of a longer term nature, which in most cases translates to stricter contractual commitments (see Womack et al. [35], Carter et al. [1]). Thus, the development of an international supplier network takes a longer term orientation with higher fixed costs in maintaining the supplier base, which further complicates the design of the sourcing network in the presence of the above-mentioned uncertainties over longer horizons. In our paper, we suggest an innovative approach to the problem, which we call the *robustness approach to international sourcing*. This approach develops the international supplier network in a way that adequately hedges the firm's performance against the worst contingency in terms of future realizable real exchange rate shocks. A detailed description of the approach, as well as its positioning relative to the current research literature in the international sourcing area, can be found in the next section.

We would like to point out that there do exist financial instruments that the firm can utilize to hedge against losses incurred by currency movements (e.g. forward contracting, currency options, futures, swaps, etc.). A risk-averse firm utilizes financial hedging instruments mainly to reduce the volatility of its cash flows and to stabilize its net earnings in the short term. This is a valuable approach when firms are not able to exploit portfolio effects or network synergies because their global supply network is inflexible and they are not capable of achieving international coordination. Contrary to financial hedging, operational hedging does not attempt to eliminate the firm's cash flow volatility but exploit it. The main challenge of operational hedging is to utilize a limited number of supply contract options to create a long-term hedge by exploiting comparative factor cost differentials on a global scale. There are two more advantages of operational hedging that are worth mentioning. The costs of financial hedging instruments increase as the planning horizon is extended; the cost of operational hedges decreases since the switching costs from one supply option to another can usually be spread over additional time periods. Furthermore, financial hedging instruments are only available for major currencies, while operational hedges are not restricted to any particular currency. For an extensive discussion on the comparison of financial hedging and operational hedging options, see Huchzermeier and Cohen [16]. It should be clear in the mind of the reader of this paper that we address issues of operational hedging against fluctuations in macroeconomic factors of the international environment.

The structure of the paper is as follows. In section 2, we discuss deterministic and stochastic approaches to the development of the international sourcing network and compare them to the robustness approach to the problem, which is formally defined in the section. In section 3, we formulate the robust international sourcing problem as a min-max version of the uncapacitated facility location problem and also establish the relationship between robust solutions and their expected cost performance.

In section 4, we present an algorithm to obtain the N best robust solutions to the international sourcing problem, and in section 5, we discuss the computational performance of the problem over a large set of randomly generated problems. Section 6 demonstrates the use of the robust international sourcing approach and an algorithm to evaluate various sourcing strategies. Finally, we summarize our results in section 7.

2. A robustness approach to international sourcing

2.1. DETERMINISTIC AND STOCHASTIC APPROACHES TO INTERNATIONAL SOURCING

The deterministic (i.e. in the absence of any data uncertainty) international supplier network design problem can be stated as follows: Given an international factory network (i.e. the plant locations are assumed fixed and given), an available set of potential suppliers internationally located (the location of the suppliers is again considered fixed and given), and demand for components to be outsourced from suppliers at each factory, select a subset of suppliers to meet the factory demands with the lowest total relevant cost over a planning horizon. The relevant costs include: (a) all fixed costs associated with developing and maintaining long-term business relationships with qualified suppliers (e.g. contractual commitments to minimum volume supply contracts, qualifying the quality level of the supplier's process, joint technology transfer/engineering/quality programs with the supplier), and (b) sourcing cost per component from the qualified supplier (this includes the supplier's production cost, a negotiated price premium, and transportation cost from the supplier to the factory). Since the above cost elements, as previously discussed, will be affected by the macroeconomic variables (exchange rates and inflation) of the countries where the supplier and the factory are located, the implicit assumption behind the deterministic approach to the international sourcing problem is that the important macroeconomic variables have assumed certain and known values over the planning horizon. The deterministic international sourcing network design problem can be modelled as a variation of the uncapacitated plant location problem (see Francis et al. [11] and Mirchandani and Francis [26] for textbook expositions of the plant location problem), as we will discuss in detail in section 3.1, and its solution will generate an optimal supplier network for the assumed macroeconomic scenario.

However, the international sourcing problem is stochastic in nature since the relevant sourcing costs are dependent on the real exchange rates between the currencies of the countries involved, and these exchange rate fluctuations cannot be predicted with certainty. A stochastic approach to the problem will involve the description of potentially realizable scenarios for the relevant macroeconomic variables, the assignment of probabilities to these scenarios, and then it will require the solution of a mathematical program that minimizes an expected cost function. Although the international sourcing network design problem, as defined in this paper, has not been addressed in the current literature, its close variant, the uncapacitated plant location, has been formulated with the use of the stochastic approach. For an extensive discussion of references and solution approaches for the uncapacitated plant location problem under uncertainty (also referred to in the literature as the "international plant location problem") and its variations, which incorporate the firm's risk preferences (through a mean-variance formulation), see the recent comprehensive review by Verter and Dincer [33]. Among the recent developments, the one that attracted the most attention is the work of Huchzermeier [17] and Huchzermeier and Cohen [16], which nicely extends previous research results (see Jucker and Carlson [18], Hodder [13], Hodder and Dincer [14], Cohen and Lee [3], and Cohen et al. [2]) by explicitly modeling the exchange rate movements over time (with the use of a stochastic diffusion process) within a stochastic dynamic programming formulation of the multi-period international supply chain design problem. The problem is of a larger scope than the one we are looking at, and it includes among other decision variables the location of factories and supply centers. This work is also within the spirit of the traditional stochastic approach and generates a supply chain design that maximizes the expected, discounted, global, after-tax value of the firm. Another influential piece of work is the recent work of Kogut and Kulatilaka [22] which, with the use of a stochastic dynamic programming model, calculates the option value of production shifting for a firm operating plants in two countries. This model also works within the traditional assumptions of the stochastic approach.

Both the deterministic and the stochastic approach can lead to suboptimal sourcing strategies. A deterministic approach to the international supplier network design problem may yield quite poor performance if the realized exchange rate and inflation values are substantially different than the assumed ones. Similarly, a stochastic approach will lead to a solution that guarantees optimal long-run performance when the potentially realizable macroeconomic scenarios are encountered repeatedly, with the frequency of appearance of each scenario according to the assumed probability distribution. The assumption of the stochastic approach might be valid for the case that irreversible structural decisions, like capital investments associated with the development of new plants, are made over long planning horizons (as, for example, in the work of Huchzermeier [17]) and/or when the decision maker is assumed to be risk neutral. However, when the quality of the decisions is evaluated on a one-time realization (or only a few realizations, not necessarily representative of the long-run performance of the system) of a macroeconomic scenario, as is the case for the international sourcing network design decision, a stochastic approach may yield suboptimal solutions for the specific realizations. The international manufacturing manager usually faces an ex post evaluation of his/her international sourcing decisions over a rather short-term period (in the range of a few months to less than two years) and with the use of cost data that reflects the actually realized (as compared to the planned or expected over the long run) macroeconomic data. This motivates the international manager to subscribe to the notion of *robust international sourcing*, i.e. development of a supplier network that is relatively insensitive to the potential realizations of the macroeconomic parameters over the planning horizon as a more appropriate approach for supplier selection in the volatile international environment. This is usually a reflection of risk averse preferences of the international manager.

The robustness approach to international sourcing searches for an international supplier network that will produce a reasonable relevant cost under any likely real exchange rate scenario for the immediate planning horizon. Our use of the term robustness is consistent with the use of the term in the strategic decision-making literature, as originally introduced by Gupta and Rosenhead [12] and Rosenhead et al. [31], and later applied in operational decision problems by Rosenblatt and Lee [30], Kouvelis et al. [23], and Daniels and Kouvelis [5]. To operationalize this approach, the international manufacturing manager or analyst needs to identify a set of likely real exchange rate scenarios, without necessarily attaching probabilities to each of these scenarios, then find a supplier network that has the best–worst case performance (with respect to the relevant costs of the firm) among all feasible networks and over all potentially realizable scenarios (i.e. the ones that can be realized with some positive probability).

Using scenarios to structure cost uncertainty allows the decision maker to describe the relationship between uncertain macroeconomic factors (such as exchange rates and inflation values) and the corresponding cost parameters of the international sourcing model based on internal knowledge and experience. Correlation among major factors that simultaneously affect the cost parameters can thus be easily accommodated. Emphasis on scenario generation also provides insight into the nature of the decision environment by requiring the decision maker to (i) identify predetermined elements of the environment, i.e. events that have occurred, or almost certainly will occur, but whose consequences have yet to unfold (e.g. governmental economic policies which have been announced and not yet implemented that will affect future macroeconomic conditions), and (ii) formalize the perceived connection among events and forces that simultaneously drive the uncertainty of multiple cost parameters to the international sourcing model (e.g. describing with the use of a systematic relationship the effects of a dollar devaluation on the exchange rates of other countries). The robustness approach crucially depends on the scenario generation process, and as such it demands from the decision maker a keener intuition about the international environment (market conditions, prior and future planned governmental actions, major political events planned to occur in the future, etc.).

Before we provide a formal definition of the concept of robustness for our international sourcing context, we would like to point out the connection of our concept to that of robust optimization as introduced in the influential paper of Mulvey et al. [27]. The authors introduce a general robust optimization framework for mathematical programs with continuous variables. This general framework is also based on a scenario generation process for the input data to the mathematical program and it models two different robustness concepts. A solution to the mathematical program is robust with respect to optimality (it is termed *solution robust*) if it remains close to optimal for any scenario realization. A solution is robust with respect to feasibility if it remains almost feasible for any scenario realization (it is termed *model robust*). Our robustness concept defined in the international sourcing context is a solution robustness concept, according to the framework of Mulvey et al. [27], and it is applied to a mathematical program with discrete variables (as opposed to the continuous variable environment of Mulvey et al. [27]). The objective function of our robust optimization model applies a *minmax regret* criterion to differentiate the cost performance of the various solutions over the given set of realizable scenarios. We defer further discussion of this issue to the next subsection.

2.2. A FORMAL DEFINITION OF THE ROBUSTNESS APPROACH

The main elements of uncertainty in our problem, which affect all relevant cost parameters, are the macroeconomic variables (exchange rate, inflation) of the various countries where factories and/or suppliers are located. We use a scenario-based approach to represent this macroeconomic uncertainty. In this paper, we deal only with uncertainty in cost parameters and not with demand uncertainty. Scenario-based approaches have been widely used and justified in the international investment planning literature (see Pomper [29] and Eppen et al. [7]). A specific macroeconomic scenario represents a potential realization of values for all macroeconomic variables of interest. Let $S = \{1,\ldots,s,\ldots,n_s\}$ be the set of all potentially realizable macroeconomic scenarios over the planning horizon. The planning horizon can be thought of either as consisting of one period, and then S is the set of all realizable scenarios in that period, or of multiple periods, and then S is the union of the sets of realizable scenarios in each period.

It is the premise of our study that over the planning horizon, the sourcing network design cannot be changed. In the modern era of global sourcing and JIT purchasing (for an extensive reference, see Carter et al. [1]), the relationships of manufacturing firms and their suppliers become tighter and of a more cooperative nature. Manufacturing firms demand on-time delivery and consistent quality from their suppliers, and in return devote significant time and resources in qualifying their suppliers by monitoring, and suggesting ways of improving, the supplier's production processes. In many cases, the manufacturing firm will get involved in extensive technology transfer, engineering design and quality improvement programs with their suppliers. On their part, the suppliers, in order to be involved in the new, more demanding business relationships, demand higher commitment levels from their customers, with minimum volume supply contracts over a planning period being widely used. In our further discussion, we use the terms a "firm develops a supplier" and "supplier development costs" to reflect the above aspects of modern sourcing.

Denote as I the set of indices of potential suppliers, and for each $i \in I$, let y_i be a binary variable that takes the value of one whenever supplier i is developed (i.e. it becomes part of the firm's supplier network), and it can be used to supply one or more manufacturing sites. On the other hand, $y_i = 0$ if supplier i is not developed and hence cannot be used. Thus, a vector $Y = (y_i, i \in I)$ indicates the suppliers that are available in the sourcing network, and let Y_s^* denote the optimal supplier selection under scenario s. We will often refer to Y as a "sourcing network" or, for brevity, we may refer to it simply as a "solution". Let $Z_s(Y)$ denote the minimum cost of supplying the manufacturing network under scenario s given that we have available the suppliers in Y. In the next section, we define explicitly $Z_s(\cdot)$. It includes the relevant cost elements mentioned in our discussion in section 2.1. A sourcing network Y is called robust if for every scenario $s \in S$ we have that

$$R_s(Y) \leq p, \tag{1}$$

where $R_s(Y)$ is given by

$$R_s(Y) = \frac{Z_s(Y) - Z_s(Y_s^*)}{Z_s(Y_s^*)} \tag{2}$$

and p is a prespecified number (for example, $p = 0.05$) that reflects desired percentage deviation in the worst case from the optimal solution. Thus, a sourcing network Y is considered robust if the cost of supplying all factories is within p of the cost induced by the best configuration of each scenario for all scenarios in S (for our example, within 5% of the optimal cost for any scenario).

The definition of robustness in (1) and (2) implies only membership, i.e. a given solution Y either passes the test and is included in the set of robust solutions, or otherwise it is excluded. Since the selection of p is made a priori, it is important for the decision maker to be able to compare or rank different robust solutions. The vector $R(Y) = (R_s(Y), s \in S)$ is an intuitively appealing measure of robustness to help us evaluate a solution Y and possibly to further discriminate among different robust solutions. Thus, we can say that a sourcing network Y_1 is *more robust* than Y_2, written as $Y_1 \geq_R Y_2$, if and only if $R(Y_1) \leq R(Y_2)$. Unfortunately, the "more robust" relation as defined above induces only a partial order on the set of robust solutions. That is, for any three solutions Y_1, Y_2 and Y_3, the relationship $\geq_R$ has the following three properties:

$$Y_i \geq_R Y_i \quad \text{for all } i, \tag{P1}$$

$$Y_1 \geq_R Y_2 \quad \text{and} \quad Y_2 \geq_R Y_3 \Rightarrow Y_1 \geq_R Y_3 \tag{P2}$$

and

$$Y_1 \geq_R Y_2 \quad \text{and} \quad Y_2 \geq_R Y_1 \Rightarrow Y_1 =_R Y_2. \tag{P3}$$

Although (P1)–(P3) can be used to establish dominance relationships among some robust solutions, they cannot rank every solution. Specificially, we can find robust solutions Y_1 and Y_2 such that property (P4) below is not satisfied.

$$\text{For any } Y_1 \text{ and } Y_2 \text{ either } Y_1 \leq_R Y_2 \text{ or } Y_2 \leq_R Y_1. \tag{P4}$$

As the number of scenarios under consideration increases, our ability to rank or establish dominance relationships among robust solutions is likely to decrease. An alternative measure of robustness is given by

$$\hat{R}(Y) = \max_{s \in S} R_s(Y). \tag{3}$$

Then we can say that a solution Y_1 is *more robust* under $\hat{R}$ than Y_2, written as $Y_1 \geq_{\hat{R}} Y_2$ if and only if $\hat{R}(Y_1) \geq \hat{R}(Y_2)$. An advantage of using the scalar $\hat{R}(Y)$ instead of the vector $R(Y)$ to measure the robustness of a solution Y is that the relationship $\geq_{\hat{R}}$ satisfies the equivalent properties (P1)–(P4). Thus, $\geq_{\hat{R}}$ completely orders the set of robust solutions. Moreover, the order induced by the relationship $\geq_R$ is preserved by $\geq_{\hat{R}}$ in the sense that for any two solutions for which $Y_1 \geq_R Y_2$ we will also have $Y_1 \geq_{\hat{R}} Y_2$; hence, the relationship $\geq_{\hat{R}}$ only "induces additional ordering" on those solutions that the relationship $\geq_R$ is unable to compare. The managerial interpretation of this ordering is that if $Y_1 \geq_{\hat{R}} Y_2$, then in the worst-case scenario, solution Y_1 will deviate from optimality less than Y_2. This, of course, does not necessarily mean that Y_1 dominates Y_2 across all scenarios.

In our modeling efforts, our objective will be to find the *N best robust solutions* to the sourcing network design problem using relationship $\geq_{\hat{R}}$ to order robust solutions. In this optimization context, the arbitrary choice of the robustness parameter p is not a critical issue. If p is selected too large, the best N robust solutions will have $\hat{R}(Y)$ significantly smaller than p. On the other hand, if p is arbitrarily selected too small, the list of robust solutions will be smaller than N; if the number of robust solutions found is not satisfactory, we have to increase p. In the next section, we first formulate the deterministic international sourcing problem as an uncapacitated facility location problem and then we proceed to the formulation of its robust version as the min-max variant of the uncapacitated facility location problem.

3. Formulation of the robust international sourcing problem

3.1. MODELING THE DETERMINISTIC INTERNATIONAL SOURCING PROBLEM AS AN UNCAPACITATED FACILITY LOCATION PROBLEM

Let us consider a firm that has an established international factory network and is contemplating the selection of suppliers to fulfill the factories' demands of components/subassemblies over a prespecified planning horizon. In introducing our notation, and for simplicity of presentation reasons only, we assume that every factory has outsourcing needs for one component/subassembly, which does not have to be the same for all factories. The extension to multiple components is straightforward and will be discussed later in the section. Let us denote by $P = \{1,\ldots,j,\ldots,n_P\}$ the set of indices of all factories in our manufacturing network. Denote by $I = \{1,\ldots,i,\ldots,n_I\}$ the set of indices for potential international suppliers, and let P_i, for $i \in I$, denote the set of indices of factories that could potentially source from supplier i. The total supply requirement of factory $j \in P$ are assumed known over the planning horizon and are denoted by D_j.

We use the superscript s to indicate the dependency of a cost parameter on a specific macroeconomic scenario s. For example, the variable cost of acquiring a unit of production from supplier i is given by v_i^s and the cost of shipping a unit of production from supplier i to factory j is denoted t_{ij}^s. The quantity t_{ij}^s can be used to represent any unit costs specific to the supplier–factory pair $i \in I$, $j \in P$ such as variable transportation costs, any applicable import/export taxes or export tax credits.

We model the supplier development costs as follows: Developing supplier i requires a fixed cost of f_i^s over the planning period, which includes costs of joint engineering, transfer of technology, and quality improvement programs. The contractual agreement with supplier i involves a minimum volume purchase of K_i units over the planning period (i.e. our purchasing quantity can be increased, but it can never be smaller than K_i units). The minimum volume requirement of any supplier, without loss of generality, is assumed to be less than the total component demand in the factory network. The way this minimum volume requirement is modelled is the following. The minimum volume of the various potential suppliers is assigned to factories (or set of factories), with the assignment criterion of minimum transportation cost being an easy one to apply without loss of optimality (as will be apparent later from the structure of the resulting mathematical program). Firms, however, are allowed at this stage to use different criteria, if so desired, to perform this preliminary assignment. For notational simplicity, we assume for a moment that every supplier's minimum volume is assigned to a single factory, and let h be the factory that supplier i's minimum volume K_i has been assigned. Thus, the total fixed cost of a supply agreement with supplier i can be computed as

$$F_i^s = f_i^s + K_i(v_i^s + t_{ih}^s). \tag{4}$$

Every factory $h \in P$ that gets assigned a minimum volume commitment K_i is substituted with "two equivalent" factories, a "*dummy factory*" h' and a "*reduced factory*" h'', with the demand requirements for these two factories being equal to

$$D_{h'} = K_i \quad \text{and} \quad D_{h''} = D_h - K_i \tag{5}$$

and the transportation cost for factory h'' being the same as for the original factory, i.e. $t_{ih''} = t_{ih}$. The variable costs of supplying all the requirements of a reduced factory h'' from supplier k are given by

$$c_{kh''} = D_{h''}(v_k^s + t_{kh}^s) \quad \text{for any } k \in I. \tag{6}$$

For a dummy factory h', the total variable costs will be

$$c_{kh'} = \begin{cases} 0 & \text{for } k = i, \\ D_{h'}(v_k^s + t_{kh'}^s) & \text{for } k \neq i. \end{cases} \tag{7}$$

The above modeling artifice allows us to handle effectively the minimum volume supply requirements without deviating from the computationally attractive mathematical structure of an uncapacitated plant location problem, as will be apparent later in the section. This artifice also does not affect the computational efficiency of the suggested solution procedure since it does not increase the number of integer variables in the formulation, which is the main source of the computational complexity of this problem.

To illustrate the above modeling approach, consider the following example. Let us assume that we have three potential suppliers $I = \{1, 2, 3\}$, and three factories $P = \{a, b, c\}$. Let $P_1 = P$, $P_2 = \{b, c\}$, and $P_3 = \{a, c\}$. The fixed costs f_i^s, minimum volume commitments K_i to each supplier, variable unit production costs v_i^s, and transportation costs per unit t_{ij}^s for a specific scenario are indicated in table 1. For the factories $j \notin P_i$, we have indicated n.a. in the corresponding entries t_{ij}^s of the table.

Table 1

Data for the example.

Supplier	f_i^s	K_i	v_i^s	t_{ia}^s	t_{ib}^s	t_{ic}^s
1	90	40	1.0	1.0	1.5	1.2
2	80	30	1.2	n.a.	1.0	1.5
3	100	80	0.8	1.5	n.a.	1.2

Let $D_a = 100$, $D_b = 120$, and $D_c = 80$. Assume also that if supplier 1 is used, the 40 units committed will be assigned to factory a; if supplier 2 is used, the 30 units committed with be assigned to factory b; and if supplier 3 is used, the 40 units of the commitment will be assigned to factory a and the remaining 40 units will be assigned to factory c. To model the allocations of supply commitments, we must break factory a into three equivalent factories denoted by a', a'', and a''', where factory a' is used to model the allocation of the 40 units committed from supplier 1, a'' is used to model the allocation of the 40 units from 3, and the demand of a''' consists of the remaining 20 units of factory a. Similarly, factory b is broken into equivalent factories b' and b'' with demands of 30 and 90 units, respectively, and factory c is broken into c' and c'' with demands of 40 units each. The resulting total fixed costs F_i^s and total variable costs c_{ij}^s for the above example are shown in table 2. To illustrate some of the computations, notice that $F_1^s = 90 + 40(1 + 1) = 170$, $F_3^s = 100 + 40(0.8 + 1.5) + 40(0.8 + 1.2) = 272$, $c_{3a'}^s = 40(0.8 + 1.5) = 92$, and $c_{1a'}^s = 0$, since the cost of sourcing these 40 units from supplier 1 is already included in F_1^s.

After preprocessing the original data as explained above, all relevant costs can be summarized for each macroeconomic scenario into a fixed cost F_i^s and a variable cost c_{ij}^s. These quantities over all realizable scenarios $s \in S$ consitute the input data to our model. Our main set of decision variables is $Y = \{y_i, i \in I\}$, with y_i being a

Table 2

Total fixed and total variable costs for the example.

Supplier	F_i^s	$c_{ia'}^s$	$c_{ia''}^s$	$c_{ia'''}^s$	$c_{ib'}^s$	$c_{ib''}^s$	$c_{ic'}^s$	$c_{ic''}^s$
1	170	0	80	40	90	225	88	88
2	146	n.a.	n.a.	n.a.	0	190	108	108
3	272	92	0	46	n.a.	n.a.	0	80

binary integer variable ($y_i = 1$ is supplier i is selected, 0 otherwise). We additionally use the variables x_{ij} to indicate the fraction of factory j's demand that is supplied from supplier i. Then, for a given macroeconomic scenario $s \in S$, we can model the deterministic international sourcing problem as an uncapacitated plant location problem as follows:

(DISP)
$$Z_s(Y_s^*) = \min \sum_{i \in I} \sum_{j \in P_i} c_{ij}^s x_{ij} + \sum_{i \in I} F_i^s y_i \tag{8}$$

$$\text{subject to} \quad \sum_{i \in I} x_{ij} \geq 1 \qquad \text{for all } j \in P, \tag{9}$$

$$x_{ij} \leq y_i \qquad \text{for all } i \in I \text{ and for all } j \in P, \tag{10}$$

$$0 \leq x_{ij} \leq 1 \qquad \text{for all } i \in I \text{ and for all } j \in P, \tag{11}$$

$$y_i \in \{0,1\} \qquad \text{for all } i \in I. \tag{12}$$

The objective function (8) simply states that we want to minimize the sum of all variable and fixed costs associated with a given scenario s. The set of constraints (9) ensures that the component requirements of every factory are satisfied. Constraints (10) are consistency constraints between the variables y_i and x_{ij} and ensure that supply shipments originate only from suppliers that have been included in the firm's supply network.

The above model can be easily extended to cover several multi-component sourcing environments. For the case that the minimum volume supply contracts are for individual components, then the sourcing problem naturally decomposes into single-component sourcing problems. Another likely case is that the minimum volume requirement will apply to all or a subset of components sourced from the supplier. This will usually be stated as a minimum requirement to be purchased from the supplier. For example, let us say that supplier i can supply components 1 and 2. The minimum volume requirement could be that a combination of quantities for the two components has to be purchased. Let us say that K_{i1} and K_{i2} are the needed quantities of component 1 and component 2. The firm will proceed to make the preprocessing assignment of each component to the factory to which it is easier to transport to (i.e. lower transportation cost) as before. This logic easily generalizes to multi-component sourcing contracts.

Below, we make a few basic observations on the structure of the uncapacitated plant location problem, which are fundamental in our further discussion. For a given sourcing network Y (i.e. the variables y_i, $i \in I$, has assumed specific values), the relevant cost of operating the supplier network Y under scenario s, $Z_s(Y)$, can be evaluated as follows:

$$Z_s(Y) = \sum_{j \in P} \left(\min_{i : j \in P_i \text{ and } y_i = 1} c_{ij}^s \right) + \sum_{i \in I} F_i^s y_i. \tag{13}$$

Relationship (13) simply states that the cost effective alternative for a given sourcing network is to use the lowest cost available supplier for each plant to supply the required components.

The Efroymson and Ray [6] algorithm is a branch-and-bound procedure, with a lower bounding procedure that exploits the above structure of the problem. Branching from a node of the tree involves the partitioning of the solution space into two by setting the value of one of the integer variables y_i to either zero or one. Thus, at a node of the branch-and-bound tree, the set of integer variables Y is partitioned into three sets:

(a) the set K_0 of integer variables whose value has already been set to zero, i.e. $K_0 = \{i : y_i = 0\}$;

(b) the set K_1 of integer variables whose value has already been set to one, i.e. $K_1 = \{k : y_i = 1\}$;

(c) the set K_2 of integer variables with as yet unspecified value, $K_2 = I \setminus \{K_0 \cup K_1\}$.

The lower bounding procedure at a specific node involves two relaxations. The first relaxation consists of adding constraints (10) over all factories j for each supplier i, and thus obtaining

$$\sum_{j \in P_i} x_{ij} \leq |P_i| y_i \quad \text{for all } i \in I. \tag{14}$$

The second relaxation consists of dropping the integrality requirement (12). The resulting problem, which consists of (8), (9), (11), and (14), is known as the weak relaxation of the uncapacitated plant location problem. To obtain the optimal solution to the weak relaxation, we need first to observe that in its optimal solution relationship, (14) will be satisfied as an equality. Thus, (8) can be rewritten for a specific node of the tree as

$$\sum_{i \in K_1} \sum_{j \in P_i} c_{ij}^s x_{ij} + \sum_{i \in K_2} \sum_{j \in P_i} \left(c_{ij}^s + \frac{1}{|P_i|} F_i^s \right) x_{ij} + \sum_{i \in K_1} F_i^s. \tag{15}$$

Let $\hat{c}_{ij}^s$ be defined as

$$\hat{c}_{ij}^s = \begin{cases} c_{ij}^s + \frac{1}{|P_i|} F_i^s & \text{for } i \in K_1, \\ c_{ij}^s & \text{otherwise.} \end{cases} \tag{16}$$

Then, the lower bound $\underline{Z}_s^h$, and the weak relaxation problem, for node h of the tree for scenario s, can be written as

(WR-DISP)
$$\underline{Z}_s^h = \sum_{i \in K_1} F_i^s + \min \sum_{i \in K_1 \cup K_2} \sum_{j \in P_i} \hat{c}_{ij}^s x_{ij} \tag{17}$$

$$\text{subject to} \quad \sum_{i \in K_1 \cup K_2} x_{ij} \geq 1 \quad \text{for all } j \in P \tag{18}$$

$$\text{and} \quad 0 \leq x_{ij} \leq 1 \quad \text{for all } j \in P \text{ and all } i \in K_1 \cup K_2. \tag{19}$$

We can easily observe that the optimal solution to the above problem is

$$x_{ij}^{s*} = \begin{cases} 1 & \text{if } i = \arg \min_{i \in K_1 \cup K_2} \left\{ \hat{c}_{ij}^s \right\}, \\ 0 & \text{otherwise,} \end{cases} \quad \text{for } j \in P. \tag{20}$$

We will use the above results extensively in our algorithmic developments.

3.2. A MIN-MAX FORMULATION OF THE ROBUST INTERNATIONAL SOURCING PROBLEM

Below, we present a formulation to obtain the best robust sourcing network over a set S of potentially realizable macroeconomic scenarios. The formulation is as follows:

(RISP)
$$\min_Y \left\{ \max_{s \in S} \frac{Z_s(Y) - Z_s(Y_s^*)}{Z_s(Y_s^*)} \right\}, \tag{21}$$

where $Z_s(Y)$ is as defined in (13) and $Z_s(Y_s^*)$ is the corresponding optimal objective value for scenario s as defined in formulation (DISP) (i.e. (8)–(12)). The optimal solution to (RISP) is denoted by Y_R. In the above formulation, it is assumed that the values $Z_s(Y_s^*)$ have already been calculated with the use of existing uncapacitated plant location algorithms (for example, Efroymson and Ray's [6] algorithm and its improved version in Khumawala [20], or with the use of Erlenkotter's [8] DUALOC algorithm and its refined dual adjustment/ascent procedure by Van Roy and Erlenkotter [32]).

An equivalent formulation for generalizing the robust sourcing network is the following:

(ERISP) $= \min z$

$$\text{subject to} \quad Z_s(Y_s^*)(z+1) \geq \sum_{i \in I} \sum_{j \in P} c_{ij}^s x_{ij} + \sum_{j \in P} F_i^s y_i \quad \text{for } s \in S; \tag{22}$$

$$(9), (10), (11), (12), \text{ and } z \geq 0.$$

Let us elaborate on this equivalence. From (21), we can always ensure the existence of a nonnegative z such that

$$Z_s(Y_s^*)(z+1) \geq \sum_{i \in I} \sum_{j \in P} c_{ij}^s x_{ij}^{s^*} + \sum_{i \in I} F_i^s y_i \quad \text{for } s \in S,$$

where $x_{ij}^{s^*}$ are given by (20). Since for any $s \in S$, we can write that there exist x_{ij}^s such that

$$Z_s(Y_s^*)(z+1) \geq \sum_{i \in I} \sum_{j \in P} c_{ij}^s x_{ij}^s \geq \sum_{i \in I} \sum_{j \in P} c_{ij}^s x_{ij}^{s^*} \quad \text{for any } s \in S,$$

we can also imply that there exists a set of continuous variables x_{ij} such that (22) is satisfied, and actually $x_{ij} = x_{ij}^{s^*}$ for some $s \in S$. This follows from the fact that (22) is satisfied as an equality for at least one $s \in S$.

Observing formulation (ERISP), we can say that the robust international sourcing problem has the structure of an uncapacitated plant location problem with the addition of the side constraints (22). This structure is fully exploited in our algorithmic developments. We can also immediately observe that (ERISP) is NP-complete, since its single scenario equivalent is the same as the uncapacitated plant location problem, which is a known NP-complete problem.

3.3. RELATIONSHIP BETWEEN ROBUST SOLUTIONS AND MINIMUM EXPECTED OPERATING COSTS

Let us first formulate the stochastic international sourcing problem. We are interested in finding the sourcing network that minimizes the total expected cost over the planning horizon. For each macroeconomic scenario $s \in S$, the probability of this scenario occurring is w_s. The expected cost of a given sourcing network Y is

$$Z(Y) = \sum_{s \in S} w_s Z_s(Y), \tag{23}$$

where $Z_s(Y)$ can be evaluated for any Y using (13). Thus, the lowest expected cost sourcing network Y^* can in principle be found by solving the following optimization problem:

$$Z = Z(Y^*) = \min_Y Z(Y). \tag{24}$$

Problem (24) is known as a two-stage stochastic optimization problem with fixed recourse (Wets [34], Kall [19]) and it proves to be computationally prohibitive for large size problems. However, our interest is in devising a bound on the deviation of the expected cost of the robust network Y_R, from the optimal expected cost Z. Below, we present a simple methodology for devising this bound.

Let us first develop a lower bound on Z. The lower bound $\underline{Z}$ is

$$\underline{Z} = \sum_{s \in S} w_s \left(\min_Y Z_s(Y) \right) \leq \min_Y \sum_{s \in S} w_s Z_s(Y) = \min_Y Z(Y) = Z. \tag{25}$$

If for our robust sourcing network Y_R it holds that

$$p = \max_{s \in S} R_s(Y_R) = \max_{s \in S} \frac{Z_s(Y_R) - Z_s(Y_s^*)}{Z_s(Y_s^*)},$$

then we must have that

$$Z_s(Y_R) \leq (1+p) Z_s(Y_s^*) \quad \text{for any } s \in S. \tag{26}$$

Therefore, it follows that

$$Z(Y_R) = \sum_{s \in S} w_s Z_s(Y_R) \leq \sum_{s \in S} w_s (1+p) Z_s(Y_s^*) = (1+p) \sum_{s \in S} w_s Z_s(Y_s^*) = (1+p)\underline{Z}. \tag{27}$$

Hence, as (27) indicates, a robust sourcing network Y_R not only has a performance guaranteed to deviate at most p from the optimal cost of any realizable macroeconomic scenario, but also has the same performance guarantee for its deviation from the optimal expected cost solution.

4. An algorithm to generate the N best robust solutions to the international sourcing problem

Below, we describe an algorithmic procedure to generate a list L containing the N best robust solutions (sourcing networks) for the international sourcing problem that are within p from the optimal cost for any realizable macroeconomic scenario. The values of p and N are specified by the decision maker. As a preprocessing step, we need to obtain the optimal solution to the deterministic international sourcing problem (DISP) for every scenario. In our computational experimentation, we used an implementation of the Efroymson and Ray [6] algorithm. However, a variety of other procedures (see chapter 3 in Mirchandani and Francis [26]) can be used as substitutes for this task (a prominent candidate is the dual descent procedure described in Erlenkotter [8]).

The algorithm we suggest requires the parallel development of the $|S|$ single scenario (DISP) branch-and-bound trees (we refer to them as scenario-trees). The execution of the robust algorithm is coordinated across all scenarios; this means that whenever a node in a tree is branched to create two child-nodes, the same corresponding node is branched in all scenario-trees. We say that a node k_s in a tree s *corresponds* to a node k_t in another tree t, denoted $k_s =_c k_t$, if these two nodes have identical positions in their respective branch-and-bound trees. Notice that the sets K_0, K_1 and K_2 of the corresonding nodes are identical. The information for node k_s (i.e. node k of scenario s) is summarized as $(K_0, K_1, K_2, \underline{Z}_s^k\ (y_i^{sk}, i \in K_2))$, where $K_0 = \{i : y_i^{sk} = 0\}$, $K_1 = \{i : y_i^{sk} = 1\}$, $K_2 = I \backslash \{K_0 \cup K_1\}$, $\underline{Z}_s^k$ is a lower bound on node k_s and $(y_i^{sk}, i \in K_2)$ is the vector of values taken by the unfixed integer variables in the evaluation of $\underline{Z}_s^k$. The procedure used to branch from a node and for evaluating its lower bound is along the lines of what Efroymson and Ray [6] propose for the uncapacitated plant location problem (for a review of the basics of the procedure, see section 3.1). Following is a description of the procedures used to branch from a node, to evaluate lower bounds for the resulting child-nodes, and all applied feasibility checks.

Branching procedure

We selected node k_s (i.e. node k of scenario s) to branch next, using the following two options: (B1) select $k_s = \arg\min_{(k,s)}\{\underline{Z}_s^k\}$, and (B2) select scenario s in a round-robin fashion, then set $k_s = \arg\min_{(k)}\{\underline{Z}_s^k\}$. In either case, the variable i to be fixed next was selected as $i = \arg\min_{i \in K_2}\{|y_i^{sk} - 0.5|\}$.

Evaluation of lower bounds

Bounds for children nodes were obtained using the weak relaxation of (DISP) as described in section 3.1.

Feasibility of the weak relaxation

If there is a plant j such that $j \notin \bigcup_{i \in K_1 \cup K_2}\{P_i\}$, then the weak relaxation (WR-DISP) has no feasible solution. This means that there is some factory demand that cannot be met by any of the currently used suppliers (i.e. in the set K_1) or the ones under consideration (i.e. set K_2).

Feasibility of the integer problem

For all $i \in K_2$ compute $y_i = (1/|P_i|)\sum_{j \in P_i} x_{ij}$. If all y_i's have integer values, then the solution is feasible for the integer program.

A detailed description of the solution procedure in a pseudo-algorithmic format follows.

ROBUST INTERNATIONAL SOURCING ALGORITHM (RISA)

Step 0. *Initialization.*

Select N and p, and initialize the list of robust solutions $L_R = \varnothing$.

For each scenario s, do:

{Compute $Z_s(Y_s^*)$.

Set $K_0 = K_1 = \varnothing$ and $K_2 = I$.
Using (WR-DISP) and (20) calculate Z_s^k and x_{ij}^{s*}.
Using (K_0, K_1, K_2, $\underline{Z}_s^0$, (y_i^s, $i \in K_2$)) create node 1.
}

Step 1. *Branching*

Select scenario $\bar{s}$, node $k_{\bar{s}}$ and variable i to branch next (as explained above), and do:
{$K_0^{[0]} = K_0 + \{i\}$, $K_1^{[0]} = K_1$, $K_2^{[0]} = K_2 - \{i\}$,
$K_0^{[1]} = K_0$, $K_1^{[1]} = K_1 + \{i\}$, $K_2^{[1]} = K_2 - \{i\}$.
}

For each node k_s corresponding to $k_{\bar{s}}$, $k_s \in C(k_{\bar{s}})$, do:
{Remove k_s from its tree.
Create node $k_s^{[0]}$ using ($K_0^{[0]}$, $K_1^{[0]}$, $K_2^{[0]}$, $\underline{Z}_s^{k_s}$, ($y_i^{k_s}$, $i \in K_2^{[0]}$)).
Create node $k_s^{[1]}$ using ($K_0^{[1]}$, $K_1^{[1]}$, $K_2^{[1]}$, $\underline{Z}_s^{k_s}$, ($y_i^{k_s}$, $i \in K_2^{[1]}$)).
Define $L_{\text{New}} = \{k_s^{[0]}, k_s^{[1]} : s \in S\}$.
}

If [$\exists k_s^{[0]} \in L_{\text{New}} : k_s^{[0]}$ is not feasible for (WR-DISP)]
then {$L_{\text{New}} = L_{\text{New}} - \{k_s^{[0]} : k_s^{[0]} \in L_{\text{New}}, s \in S\}$
Go to step 3.
}
else {Go to step 2}.

Step 2. *Robustness test for* [0] *nodes.*

For $k_s^{[0]} \in L_{\text{New}}$ evaluate $\underline{Z}_s^{k[0]}$ and ($y_i^{k[0]}$, $i \in K_2^{[0]}$) using (WR-DISP) and (20).
If [$(\underline{Z}_s^{k[0]} - Z_s(Y_s^*))/Z_s(Y_s^*) > p$ for any $s \in S$]
then {$L_{\text{New}} = L_{\text{New}} - \{k_s^{[0]} : s \in S\}$}.

Step 3. *Robustness test for* [1] *nodes.*

For $k_s^{[1]} \in L_{\text{New}}$ evaluate $\underline{Z}_s^{k[1]}$ and ($y_i^{k[1]}$, $i \in K_2^{[1]}$) using (WR-DISP) and (20).
If [$(\underline{Z}_s^{k[1]} - Z_s(y_s^*))/Z_s(y_s^*) > p$ for any $s \in S$]
then {$L_{\text{New}} = L_{\text{New}} - \{k_s^{k[1]} : s \in S\}$}.
If [$L_{\text{New}} = \varnothing$] then {Go to step 1}.
Place all nodes $k \in L_{\text{New}}$ in their respective trees.
Set $L_{\text{Int}} = \{k : k \in L_{\text{New}}$ and $y_i^k \in \{0, 1\}$ for all $i \in I\}$.
Go to step 4.

Step 4. *Robustness test for integral solutons.*

For all $k \in L_{\text{Int}}$ do:

{For all $s \in S$ evaluate $Z_s(Y^k)$ using (13)}

If $[(Z_s(Y^k) - Z_s(Y_s^*))/Z_s(Y_s^*) > p$ for any $s \in S]$

then $\{L_{\text{Int}} = L_{\text{Int}} - \{k\}\}$.

If $[L_{\text{Int}} = \varnothing]$

then {Go to step 1}.

else {Go to step 5}.

Step 5. *Update list L_R of robust solutions.*

For all $k \in L_{\text{Int}}$ do:

[For all $s \in S$ do:

{Compute $\rho_s^k = (Z_s(Y^k) - Z_s(Y_s^*))/Z_s(Y_s^*)\}$.

Compute $R^k = \max_s \rho_s^k$.

If $[R^k < p]$ then $\{L_R = L_R + \{k\}\}$

}

If $[|L_R| > N]$

then {Drop the $|L_R| - N$ solutions k with largest R^k, and also drop all their corresponding nodes in all trees,

Set $p = \max_{k \in L_R}\{R^k\}$

}

Go to step 1.

Observe that since we always branch from corresponding nodes in all branch-and-bound trees, and whenever a node is discarded all corresponding nodes are discarded in all trees, all trees have the same structure at any point during the execution of the algorithm. When the algorithm terminates, all tree lists are empty.

Notice that the algorithm only eliminates nodes from the different scenario trees when a given lower bound does not meet the robustness criterion (step 2), or when we tighten the robustness criterion (reduce p) because we have already identified N robust solutions (step 4). Hence, when the algorithm finishes executing, for a given prespecified robustness parameter p, it will either have identified the best N robust solutions, or if it identifies only $n < N$, possibly $n = 0$ robust solutions, then we can guarantee that these are the only robust solutions for the given p. In this latter case, the results of the algorithm will indicate that the original robustness requirements, as determined by p, were too stringent given the degree of uncertainty in the data. The next step for the analyst is to increase the value of p and re-execute the algorithm.

5. Computational performance of (RISA)

5.1. DATA SET DEVELOPMENT FOR COMPUTATIONAL TESTING

In this section, we describe the data sets that were created to test the viability of the robustness concept and the efficiency of the algorithm. We tested the algorithm on three problem sizes: a set of problems with ten potential suppliers and twenty factories, a second set with fifteen potential suppliers and thirty factories, and a third set with twenty potential suppliers and forty factories. These problem sizes will be referred to subsequently as 10–20, 15–30, and 20–40 problems. To obtain robust solutions, these problems were tested under a number of real exchange rate scenarios. Specifically, the robust algorithm was tested with five, twenty, and thirty operation scenarios on each problem. For each problem, we first generated a base case data set, then this set was changed to reflect the differences between scenarios. All the data sets for the test problems were generated randomly.

5.1.1. Generation of base case problem

The first step in creating a test problem consisted of generating the distance matrix between suppliers and factories. This was accomplished by generating uniformly distributed points in a unit square; each point corresponded to the location of either a supplier or a factory. The transportation cost t_{ij} for each supplier i and factory j was obtained by rescaling the Euclidean distance between their corresponding points in the unit square by a factor of $\hat{t}$. For each supplier i, we randomly generated a unit variable cost v_i according to a uniform distribution $U(\underline{v}, \overline{v})$. The demand requirements of each factory D_j were generated according to a uniform distribution $U(\underline{D}, \overline{D})$. To incorporate the modeling device of representing purchase commitments to some suppliers as fixed costs, we selected a subset of suppliers, and for each supplier in the subset, we selected a factory to assign to the supplier (this is the equivalent of a dummy plant as described in section 3), and for this factory and supplier, we selected the corresponding supply cost as zero. Then for all suppliers, we generated their fixed cost as a uniformly distributed random variable $F_i \sim U(\underline{F}, \overline{F})$. Since the fixed costs include part of the supply costs of a customer, in each problem the parameters were selected so that the fixed costs F_i's were of the same order of magnitude as the variable costs c_{ij}. Specifically, in generating our base case problem, we used $\hat{t} = 1.5$, $\overline{F} = 200$, $\underline{F} = 100$, $\underline{D} = 20$, $\overline{D} = 30$, $\underline{v} = 10$, and $\overline{v} = 20$.

5.1.2. Generation of scenarios

As was illustrated in section 1, the fluctuations of the exchange rates do not necessarily correspond to short-term changes in the local prices. Figures 1 and 2 show that it is possible for some countries to have increases/decreases in the relative costs of production of the order of 25% over short periods of time (one or two years).

To represent this phenomenon in our data, we took a problem generated as above as a base case (scenario 1) and then altered its cost structure to generate the different scenarios. This was accomplished by generating a random and independent factor q_i^s for each supplier i and for each scenario s, with $q_i^s \sim U(\underline{\alpha}, \overline{\alpha})$, with $\underline{\alpha} = 1/1.3$ and $\overline{\alpha} = 1.3$; this factor was assumed to be 1 for the first scenario, i.e. $q_i^s = 1$ for all suppliers i and for $s = 1$. By multiplying all base cost data times this factor, we are representing price changes that can vary up to $\pm 30\%$ for each supplier. Thus, the costs for each scenario were obtained by computing $F_i^s = q_i^s F_i$, $v_i^s = q_i^s v_i$, and $c_{ij}^s = D_j(t_{ij} + v_i^s)$. In the next section, we report our computational results.

5.2. COMPUTATION RESULTS

We tested the robust algorithm on seven groups of ten sample problems for each group. The computational results are summarized in table 3. With respect to the number of scenarios, we tested problems with 5, 20, and 30 different scenarios. In all cases, we started the algorithm with a value for the robustness parameter $p = 0.20$, and we set $N = 10$. That is, initially any solution within 20% of the optimal across all scenarios is considered robust and we required from the algorithm to list the 10 best robust solutions. We tested two selection rules for the next scenario tree to

Table 3

Computational performance of (RISA). Columns 2 and 3 report average, over 10 sample problems, run times on a SUN workstation for two different branching selection criteria (i.e. which scenario tree to branch on next). The first column reports the average, over 10 sample problems, worst-case percentage deviation from optimality for the 10th robust solution.

			Avg. CPU time (sec) Branching select. crit.	
	Best robust	10th robust	Sequential	Smallest cost
5 scenarios				
10 candidate suppliers (10–20)*	3.8	9.6	2.4	1.8
15 candidate suppliers (15–30)	2.4	4.7	11.5	8.5
20 candidate suppliers (20–40)	2.0	3.5	27.1	35.1
20 scenarios				
10 candidate suppliers (10–20)	5.3	10.3	19.3	20.1
15 candidate suppliers (15–30)	4.9	7.7	96.0	127.1
30 scenarios				
10 candidate suppliers (10–20)	6.2	11.4	43.5	44.7
15 candidate suppliers (15–30)	6.2	8.0	187.8	208.0

*10–20: 10 candidate suppliers, 20 factories.

branch. The first rule is a round-robin selection discipline in which each time an algorithm executes, the branching step selects the node to branch next from a different scenario tree in a sequential fashion. The second rule selects the scenario tree having the smallest lower bound on its nodes. The average run times of these two selection rules are reported in the last two columns of table 3. The sequential strategy proved to be superior to the lowest cost strategy. However, as our computational results indicate, run times are not an issue for the problem sizes considered, and thus implementation of either of the two selection rules is computationally effective. Problems with 15 candidate suppliers and 30 operating scenarios can be solved on the average in about 3 minutes (187.8 seconds) with a SUN workstation.

As we can see from table 3, the average worst-case suboptimality of the 10th best robust solution is of the order of 10% for the problem with 10 potential suppliers, and of the order of 7% or 8% for problems with 15 suppliers. In most cases, the performance of the best robust solution is 45% better than that of the 10th best robust solution (i.e. in the range of 2–6% worst-case deviation from optimality over all scenarios). We observed a significant improvement in the robustness of the solutions as we increased the number of candidate suppliers for a fixed number of scenarios. As the number of scenarios increased, the robustness of the solutions decreased as expected. However, the decrease is not as drastic when going from 20 to 30 scenarios; for example, for the problem with 15 suppliers, the robustness worsened from 7.7% to only 8% when we added 10 additional scenarios.

As the number of suppliers increases, performance (CPU time) deteriorates significantly. This is due to the computational complexity of (DISP). However, this does not represent a significant limitation to the applicability of this model. The number of potential suppliers in practice is limited using prequalification criteria, as mentioned in Carter et al. [1] and Womack et al. [35], so that in practice we expect that the number of qualified potential suppliers is within computationally feasible bounds (in our experience, programs up to 30 suppliers can be handled with reasonable computational effort).

To see how the tun time is affected by N and the initial selection of p, we solved the set of problems in table 3 with 10 suppliers, 20 factories, and 20 scenarios using the sequential algorithm for different combinations of N and p. In table 4, we report the resulting CPU times. As we can observe from the table, larger initial selections of p (respectively, N) lead to larger average CPU times. A more interesting effect is the interaction of N and p. A large initial value of p will not increase CPU times as much if a small value of N is selected. This is because for small N values, the algorithm will reduce p (step 4). Similarly, if the value of p is small, the algorithm will eliminate faster incumbent nodes; the potential problem is that the algorithm may find fewer robust solutions than needed. From table 4, we can observe that there is a reinforcing effect of increasing values of p and N simultaneously. Using $(p, N) = (0.10, 10)$ as a base case, and increasing N to 20 increases run time by 35% (from 14.4 to 19.4 seconds), while increasing p from 0.10 to 0.20 increases run time

Table 4

Computational performance (measured in CPU sec.) of (RISA)for different selections of N and p.

Initial p	Number of robust solutions (N) 1	5	10	20
0.05	3.2	4.1	4.7*	4.7*
0.10	3.4	9.8	14.4	19.4
0.20	4.8	13.2	19.2	39.1

*Less than 10 robust solutions found.

by 33% (from 14.4 to 19.2 seconds). However, if both N and p are increased to 20 and 0.20, respectively, run time increases by 172% (from 14.4 to 39.1 seconds). A similar (though smaller) effect is observed by using $(p, N) = (0.05, 10)$ as a base case.

These experimental results suggest that when CPU times become a concern, we must select either p or N reasonably small. Simultaneous selection of large p and N may be computationally prohibitive.

6. Managerial uses of the robust international sourcing algorithm

In this section, we further discuss how the international manager can use the Robust International Sourcing approach and the (RISA) algorithm to evaluate the performance of various sourcing strategies. We use an example to demonstrate how decisions made using our model have significantly better performance than some ad-hoc decision rules often used to setup sourcing networks. The main observations stated in this example were found to be true over all data sets used in our previously described computational study.

One of the most common heuristic rules is a myopic policy that develops the sourcing network using short-term performance information of a set of qualified suppliers. In most cases, the sourcing network has more than one supplier, since selecting a single supplier for a network of factories is a suboptimal strategy even if the future costs are known with certainty. Differences in the cost of transportation from supplier locations to different factories alone make desirable the presence of more than one supplier in the network. On the other hand, for strategic reasons, it is not desirable to establish close relationships with more than a few suppliers. Thus, the supplier selection process ends up in evaluating the best K (with K being company specific; for purposes of our example, let us say four) suppliers and then proceed to establish close relationships with them. The problem with this strategy is that in making the sourcing decisions, we evaluate the suppliers under a single macroeconomic scenario. Even worse, the data used for evaluation purposes is more indicative of the

Table 5

Percent of increase in operating costs with respect to the optimal cost of each operating scenario.

	Scenarios						
	1	2	3	4	5	Max	Avg.
Best supplier	7.6	12.3	9.1	60.0	9.7	60.0	19.7
2nd best supplier	30.6	27.1	49.1	13.9	55.1	55.1	35.2
3rd best supplier	66.3	27.0	37.7	9.3	39.6	66.3	36.0
4th best supplier	67.2	17.1	62.3	45.2	56.2	67.2	49.6
Four best suppliers	13.4	12.8	14.1	12.3	14.4	14.4	13.4
Four most robust suppliers	5.0	4.4	3.4	4.0	3.9	5.0	4.1

past than the future. Actual operating conditions in the future may be very different from the ones used to select the suppliers, since the realization of the real exchange rate is highly likely to be substantially different. To illustrate the advantages of using our modeling approach and algorithm, and to demonstrate the significant suboptimality of the above heuristic sourcing strategy, we used a randomly generated example with 10 potential suppliers and 20 factories, and represented the future uncertainty with 5 operating scenarios. The data for the example was generated using the procedure described in section 5.1. For now, it suffices to say that the data was generated randomly as explained in section 5.

The results of the example are summarized in table 5. The base case scenario, also constructed to be the expected value scenario (i.e. the cost data of this scenario is also the average cost data over all scenarios), is scenario 1 in the table. From the table, we can see that by selecting the best single supplier for scenario 1 we end up with an operating cost 7.6% greater than that of the optimal supplier configuration. This reinforces the point on the suboptimality of single-supplier strategies. Moreover, if we analyze the performance of the selected supplier over the five scenarios considered, we can see that in the worst case its costs exceeds by 60% the performance of the optimal, and on the average over the five scenarios it costs 19.7% more than the optimal. The overall performance of the other individual supplier selections (e.g. 2nd, 3rd, and 4th best suppliers for scenario 1) have comparable worst-case performance but significantly worse average performance over the five scenarios. We need to note that the poor performance of these supplier selections is somewhat exaggerated since we are comparing them against a policy (the one that uses the optimal sourcing network for each scenario) which cannot be implemented since it assumes a prior knowledge about the actually realized scenario in the future; in other words, the basis of our comparison is the lower bound to the optimal cost developed in section 3.3.

From table 5, we can see that when the four best suppliers for scenario 1 are selected, instead of only one supplier, we obtain a significant improvement in performance of the sourcing network, both average and worst case. The example so far confirms the wisdom of selecting several suppliers as a way to hedge operational exchange rate exposure. Moreover, as we can observe in the last row of table 5, if instead of selecting the four best suppliers by analyzing only the base case scenario we select the four most robust suppliers over the five scenarios, by using a variation of the algorithm in section 4, the worst case and average cost performance of the sourcing network improves by over 9%. Observe that even though we are comparing the performance of the sourcing network against an unattainable lower bound, the worst case and average cost deviation from it are only 5% and 4.1%, respectively. If in the above example we do not restrict the number of suppliers to 4, the algorithm finds the best robust solution with a worst-case deviation of 1%. This solution uses six suppliers. This clearly demonstrates the substantial advantages obtained through the use of the robustness approach to sourcing.

As a minor technical point, the robust sourcing policy with four suppliers illustrated above has the additional restriction that no more than K suppliers (in this case, $K = 4$) are used, and in order to generate it we needed a minor modification of the robust algorithm. This was accomplished by modifying step 1 so that whenever nodes in which an additional supplier's variable is fixed as one, the cardinality of the set K_1 is verified and the newly created nodes are discarded if the cardinality of K_1 exceeds K.

7. Concluding remarks

The appropriate development of international supplier networks to hedge against future real exchange rate shocks is a challenging task for multinational firms practising global sourcing. The robustness approach to international sourcing attempts to develop the sourcing network in a way that a reasonable cost performance is achieved for any likely real exchange rate scenario over a short-term planning horizon. The attractive features of this approach are:

(a) It does not require input of probabilistic information about the future real exchange rate scenarios.

(b) The algorithmic development (RISA) generates the N best robust sourcing networks for reasonably sized international factory networks and for a reasonable number of realizable scenarios. The computational efficiency and effectiveness of the approach is not determined by the number of factories in the network, but by the number of suppliers. Since successful global firms, according to the spirit of Total Quality Management (TQM) apply strict prequalification steps for suppliers, the algorithm will have to be executed only for the "short list" of prequalified suppliers. The increase in the number of potential scenarios leads to only linear increases to the computational times, thus allowing mainframe executions of the algorithm to solve realistically large problems for an adequate number of future scenarios.

(c) The generated sourcing networks not only have a reasonable cost performance over all realizable scenarios, but also exhibit a substantially better performance in terms of their expected cost behavior over longer horizons.

Our computational study on problem sets with extensive variation in the cost data of the future scenarios (a range of 60% around a base case data set), significantly larger than what one can expect to find in data sets encountered in practice, indicates that a substantial number of robust sourcing networks can be found within a few percentage points deviation from the optimal cost over a large number of scenarios. In other words, it is a realistic objective for the international manager to search for robust sourcing networks.

Our research so far indicates that the robustness approach is a viable alternative for international operational decision-making environments with significant data uncertainty. A promising future research avenue is the application of the approach to other problems, such as capacity acquisition and plant location decisions, in an international context.

Acknowledgements

We gratefully acknowledge the help of our research assistants Milind Sohoni and Krisnamurthy Venkataraman in coding the algorithm and executing the computational tests reported in this paper. We are particularly grateful to the Guest Editor, Dr. Stavros Zenios, for his careful treatment of our paper and for allowing us to undertake a substantial revision of the originally submitted draft. We also appreciate the thoughtful suggestions of the two anonymous reviewers of the paper. This research was funded in part by ARP/ATP Grant No. 003658-339 from the Texas Higher Education Coordinating Board. The second author acknowledges support by a grant from CIBER at the Fuqua School of Business, Duke University.

References

[1] J.R. Carter, R. Narashimhan and S.K. Vickery, *International Sourcing for Manufacturing Operations*, Monograph No. 3 (Operations Management Association, Waco, TX, 1988).

[2] M.A. Cohen, M. Fisher and R. Jaikumar, International manufacturing and distribution networks, in: *Managing International Manufacturing*, ed. K. Ferdows (1989) pp. 67–94.

[3] M.A. Cohen and H.L. Lee, Strategic analysis of integrated production – distribution systems: Models and methods, Oper. Res. 36(1988)216–228.

[4] J.S. Dalby and M.T. Flaherty, International financial data, Harvard Business School Note 9-689-039 (1991).

[5] R.L. Daniels and P. Kouvelis, Robust scheduling to hedge against processing time uncertainty in single-stage production, Manag. Sci. 41(1995)363–376.
[6] M.A. Efroymson and T.L. Ray, A branch and bound algorithm for plant location, Oper. Res. 14(1966)361–368.
[7] G. Eppen, K. Martin and L. Schrage, A scenario approach to capacity planning, Oper. Res. 37(1989)517–527.
[8] D. Erlenkotter, A dual-based procedure for uncapacitated facility location, Oper. Res. 26(1978) 992–1009.
[9] K. Ferdows, *Managing International Manufacturing* (North-Holland, Amsterdam, 1989).
[10] T. Flaherty, International sourcing: Beyond catalog shopping and franchising, in: *Managing International Manufacturing*, ed. K. Ferdows (1989) pp. 95–124.
[11] R.L. Francis, L.F. McGinnis, Jr. and J.A. White, *Facility Layout and Location: An Analytical Approach* (Prentice–Hall, Englewood Cliffs, NJ, 1992).
[12] S.K. Gupta and J. Rosenhead, Robustness in sequantial investment decisions, Manag. Sci. 15(1968)818–820.
[13] J.E. Hodder, Financial market approaches to facility location under uncertainty, Oper. Res. 32(1984)1374–1380.
[14] J.E. Hodder and M.C. Dincer, A multifactor model for international plant location and financing under uncertainty, Comp. Oper. Res. 13(1986)601–609.
[15] P. Hooper and C.L. Mann, Exchange rate pass-through in the 1980's: The case of U.S. imports of manufacturers, Brookings Papers on Economic Activity 1(1989)297–337.
[16] A. Huchzermeier and M.A. Cohen, Valuing operational flexibility under exchange rate, Working Paper, Graduate School of Business, University of Chicago (1992).
[17] A. Huchzermeier, Global manufacturing strategy planning under exchange rate uncertainty, Ph.D. Thesis, Decision Science Department, Wharton School, University of Pennsylvania (1991).
[18] J.V. Jucker and R.C. Carlson, The simple plant location problem under uncertainty, Oper. Res. 24(1976)1045–1055.
[19] P. Kall, *Stochastic Linear Programming* (Springer, Berlin, 1976).
[20] B.M. Khumawala, An efficient branch and bound algorithm for the warehouse location problem, Manag. Sci. 18(1972)718–731.
[21] B. Kogut, Designing global strategies: Profiting from operational flexibility, Sloan Manag. Rev. 27–38 (Fall, 1985).
[22] B. Kogut and N. Kulatilaka, Rating flexibility, global manufacturing, and the option value of a multinational network, Working Paper, Wharton School, University of Pennsylvania (1992).
[23] P. Kouvelis, A.A. Kurawarwala and G.J. Gutierrez, Algorithms for robust single and multiple period layout planning for manufacturing systems, Euro. J. Oper. Res. 63(1992)287–303.
[24] D.R. Lessard and J.B. Lightston, Volatile exchange rates can put operations at risk, Harvard Business Rev. 107–114 (July-August, 1986).
[25] M.E. McGrath and R.W. Hoole, Manufacturing's new economics of scale, Harvard Business Rev. 94–102 (May-June, 1992).
[26] P.B. Mirchandani and R.L. Francis, *Discrete Location Theory* (Wiley, 1990).
[27] J.M. Mulvey, R.J. Vanderbei and S.A. Zenios, Robust optimization of large-scale systems: General modeling framework and computations, Oper. Res. 43(1995)264–281.
[28] M.D. Oliff, J.S. Arpan and F.L. Dubois, Global manufacturing rationalization: The design and management of international factory networks, in: *Managing International Manufacturing*, ed. K. Ferdows (1989) pp. 41–66.
[29] C.L. Pomper, *International Investment Planning: An Integrated Approach* (North-Holland, Amsterdam, 1976).
[30] M.J. Rosenblatt and H.L. Lee, A robustness approach to facilities design, Int. J. Prod. Res. 25(1987)479–486.

[31] J. Rosenhead, M. Elton and S.K. Gupta, Robustness and optimality as criteria for strategic decisions, Oper. Res. Quart. 23(1972)413–430.
[32] T.J. Van Roy and D. Erlenkotter, A dual-based procedure for dynamic facility location, Manag. Sci. 28(1982)1091–1105.
[33] V. Verter and M.C. Dincer, An integrated evaluation of facility location, capacity acquisition and technology selection for designing global manufacturing strategies, Euro. J. Oper. Res. 60(1992) 1–18.
[34] R.J-B Wets, Stochastic programs with fixed recourse: The equivalent deterministic problem, SIAM Rev. 16(1974)309–339.
[35] J.P. Womack, D.T. Jones and D. Roos, *The Machine that Changed the World* (Rawson Assoc., New York, 1990).