Identifying Robust Portfolios of Suppliers: A Sustainability Selection and Development Perspective

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Abstract

The initial selection and development of suppliers is a critical and increasingly complex component of organizational supply chains. In recent years sustainability issues have played an increasing role in making these decisions, though there has been limited activity in the literature in this regard. We develop an optimization model that simultaneously addresses supplier selection, supplier development, and sustainability considerations. Sustainability is integrated in the form of supplier sustainability ratings and sustainable supplier development through investment and training budgets. To handle the considerable complexity concerning such decisions, we demonstrate a recent algorithmic approach that can identify a portfolio (set) of multiple high-quality and yet collectively diverse solutions. This approach is carried out on a selection of randomly generated, representative test instances. Encouraging computational results and managerial implications are analyzed and discussed.

1 Introduction

As industrial competition continues globalizing, intrepid orga-nizations have sought to strengthen their local and international supply networks to maintain their competitive positions. Strategic partnering and development play a central role in building these networks. Recognition of the central role that suppliers and supply chains have in organizational competitiveness has further under-scored the importance of supplier selection, maintenance, and development in managerial and organizational decision making. In response to this recognition and evolving competitive environ-ment, supplier selection, vendor management, and supplier development analytical studies have seen marked growth in recent years.

In addition to issues of economic and global competitiveness, there are intensifying stakeholder pressures to ensure that social and environmental sustainability dimensions, from the triple bot-tom line definition of sustainability, are taken into consideration when supply chain management efforts are implemented. These additional sustainability concerns introduce greater uncertainty and complexity to organizational supply chain management and decision making. Multiple functions, decision makers, and organizations become involved in supporting dynamic supply chain decisions. Decision tools that can support managers in this continuously evolving environment are increasingly desirable (Brandenburg et al., 2014).

The need for analytical decision research is growing and many different research directions and gaps still remain for general supplier management modeling (Ho et al., 2010), and more specifically for sustainable and green supply chain management modeling (Brandenburg et al., 2014; Govindan, et al., 2013). In addition to standalone analytical models, integrative models that can coherently and effectively address the multiple decision and managerial dimensions of supply chains are of great value.

The joint evaluation of supplier selection and development has seen limited, if any, analytical or decision modeling research (Meisel, 2012). Recent works on separate analytical and decision modeling for supplier selection, and to a much lesser extent sup-plier development, have seen increases. Even when excluding sustainability dimensions, the authors are unaware of any joint consideration of these issues. Thus, given the recent importance in sustainability, supplier selection and development, our investiga-tion seeks to contribute to the literature by building on sustainable supplier selection and development research.

We address this gap by developing and evaluating a new opti-mization model that embodies the dual stages of supplier selection and supplier development. An equally significant contribution is due to our subsequent analysis on test instances of this model using a recent algorithmic approach that can identify a portfolio (set) of multiple high-quality and yet collectively diverse solutions (Trapp and Konrad, 2013). Competitive, natural environment, and social uncertainties require careful and simultaneous examination of multiple suppliers by management to help reduce the risk in sup-plier selection and development. Consideration of the dynamic, multiple stakeholder environment requires some flexibility in the selection of the supplier portfolio. That is, an ultimate decision may not always be the best for each and every decision maker or sce-nario, especially given the many implicit and explicit dimensions of the decision environment. So, while a diverse set of solutions is highly desirable in this context, at the same time these solutions should not sacrifice on the solution quality, in terms of business and/or sustainability measures. The approach can, while main-taining high quality, allow for a variety of diverse solutions from which decision makers may further refine their choices.

The remainder of the paper is structured as follows. In the next section a foundation of research and practice literature related to the topics of supplier management and sustainability are over-viewed. The mathematical formulation and methodology are then introduced. Next an illustrative example is discussed that outlines a small instance and how the solution approach can aid in identifying alternate solutions that are both high-quality and diverse. Computational experiments are subsequently reported with some initial observations concerning the results presented. A discussion and conclusion follows with clear practical and research implica-tions. The conclusion also provides an overview of the limitations and directions for future research.

2 Background and Literature Review

We provide a review of the general supply chain modelling and supplier selection literature to properly situate our study in its greater context. This background will help inform the development and evaluation of the analytical model that we subsequently introduce. We also survey related works that focus on the integration of sustainability into supplier selection and development. The practical and managerial issues facing the supplier portfolio selection process are also introduced and set the stage for practical application of the aforementioned tool, which we will return to in subsequent discussions.

2.1 Supply Chain Management – Supplier Selection and Development

The supply chain management literature includes a number of issues which need attention for maintaining a strategic and competitive supply chain, including management concerns such as (Talluri and Narasimhan, 2004):

- Which suppliers should be considered for partnering?
- Which suppliers should be part of supplier development initiatives?
- Which suppliers must be removed from the supply base?
- How can weak suppliers improve their performance?
- How can firms effectively allocate resources to supplier development programs?

Among these, in this paper we focus on supplier partnering/ selection and development. While some have defined supplier development solely as supplier selection (Chan and Kumar, 2007), supplier development extends beyond supplier selection. Specifically, supplier development also includes aiding suppliers through investment of various resources either by a buyer, or jointly with a supplier, to improve supplier capabilities and performance (Praxmarer-Carus et al., 2013). Yet, supplier selection criteria can play a role in further evaluation of supplier development (Hahn et al., 1990; Lee et al., 2001).

The number of supplier selection models has increased exponentially over the past couple of decades (De Boer et al., 2001; Ho et al., 2010). Many modelling approaches have been utilized from basic vendor selection optimization models with traditional business criteria (e.g. Sarkis and Semple, 1999) to integrated techniques that utilize multiple methods and address a wide variety of tangible and intangible criteria (e.g. Kasirian et al., 2013). In many cases supplier selection decision modelling has transcended the traditional boundaries of deciding which supplier(s) to select. For example, the supplier selection decision has been integrated with benchmarking and improvement (Liu et al., 2000), production planning constraints (Ghodsypour and O'Brien, 2001), inventory management considerations (Aissaoui et al., 2007; Xia and Wu, 2007), purchase/procurement quantities (Ting and Cho, 2008; Zhang and Chen, 2013), supplier failure (Ruiz-Torres et al., 2013), and sustainability/environment issues (Genovese et al., 2013; Govindan et al., 2013a).

Outside of supplier benchmarking and some post-hoc evaluation using similar criteria, supplier selection models have over-looked the explicit integration of supplier development issues (Mesquita et al., 2008). This oversight is unfortunate, as supplier development is important for a variety of reasons. These reasons range from benefits to the focal organization, competitive posture improvement, supplier development through higher quality, shortened product development cycles, and lower costs (Brennan and Turnbull, 1999), to overall improvement in supplier satisfaction, capability, flexibility and profitability (Carr et al., 2008; Praxmarer-Carus et al., 2013), to improvement of trust and general collaborative capabilities of the focal company supplier relationship (Blonska et al., 2013; Krause et al., 2007). The breadth of these benefits exemplifies some of the complexities involved in making decisions in this environment and the need for tools to help managers make difficult decisions.

While sustainable supply chain management has many of the above traits in common with general supplier selection and supplier development, it also has additional considerations. We next provide an overview of some of these key features and considerations.

2.2 Sustainable Supply Chain Management – Supplier Selection and Development

Although no consensus definition exists for green and sustain-able supply chains, sustainable supply chain management can be defined as incorporating various dimensions of social, economic, and environmental sustainability into supply chain management (Ahi and Searcy, 2013). Sustainability has been defined as an intergenerational philosophy (Bruntland, 1987), i.e. using resources today without compromising the needs of future generations, and through the triple-bottom-line concept of integrating environ-mental, social, and economic dimensions into organizational decision making (Elkington, 1998).

The additional cross-functional and inter-organizational characteristics of sustainable supply chain management complicate even the simplest sustainability-oriented decisions, though this complexity is dependent on the defined boundaries of a particular supply chain (Sarkis, 2012). The integration of environmental sustainability practices into organizations range from reactive activities in response to regulations, e.g. management of hazardous materials, to more proactive activities that include developing plans to gain competitive advantages from greener practices, such as eco-design and green marketing (Buysse and Verbeke, 2003; Wu et al., 2014). The importance of extending these green practices to adoption by suppliers has not been lost in the literature. The UN Global Compact in a recent survey of over 800 executives found supply chain management issues as a top barrier to general corporate sustainability (United Nations Global Compact, 2013). Green supplier development can take on many activities including supplier development through training and investment. Such supplier training and development is becoming increasingly important and prevalent and may include basics such as learning how to handle toxic chemicals delivery, recycling policy and take-back procedures) to more proactive and complex procedures such as standards adoption, eco-design, new technology adoption, and green marketing campaigns (Gottberg et al., 2006;

Lee and Bony, 2008; Lee and Kim, 2011; Scruggs, 2013; Zhu et al., 2011; Wong et al., 2012).

While sustainable supplier-development investments can focus on specific capital equipment investments, they also include costs of training, knowledge sharing, and other more intangible items and risks (Akamp and Müller, 2013; Fu et al., 2012; Dou et al., 2014). Green-supplier-development practices have been categorized into three groupings (Bai and Sarkis, 2010; Fu et al., 2012): 1. Green knowledge transfer and communication; 2. Investment and resource transfer; and 3. Management and organizational practices. The first category may include programs such as training suppliers on the issues of environmental cost controls, providing technical expertise to suppliers, eco-design, product development training, setting environmental performance targets for suppliers, and joint and team problem solving on environmental issues. Investment and resource transfer under green-supplier-development practices include transferring employees with environmental expertise to suppliers, rewarding suppliers for better environmental performance, and financing suppliers' major environmental capital expenditures. The third category can comprise aspects such as requiring and aiding in acquiring ISO 14000 certification for sup-pliers, setting long-term contracts that include environmental dimensions, building top management commitment for greening the supply chain, and developing a formal process for supplier development for suppliers' suppliers.

As can be seen, green supplier development practices cover a broad range of possible activities. Since organizational resources are generally limited, identifying which suppliers to invest in to develop sustainability capabilities, or selecting suppliers with these capabilities, is an important strategic decision for the buyer firms. Sustainable supplier selection models currently assume that the sustainability capabilities are a given and thus development is not explicitly considered. Within supplier selection there may be necessary investments in suppliers to improve their sustainability capabilities. Yet not all suppliers will require the same level of training, equipment, organizational, or knowledge sharing in the development of their sustainability capabilities. Thus, selection of sustainable suppliers, in a sustainable supplier development context, should include the costs required to bring suppliers 'up to speed' on sustainability capabilities. Yet, models that include both sustainable supplier development and selection do not exist.

Although sustainability integration into supplier selection is still in its infancy, a number of formal models addressing sustainable supplier selection do exist (Genovese et al., 2013; Govindan et al., 2013a). As is the case with the general supplier selection literature, the sustainability-based supplier selection models have yet to be integrated with supplier development concerns. Formal quantitative models for general supplier development have been quite limited (Bai and Sarkis, 2010; Dou et al., 2014), let alone those that incorporate aspects of sustainability. Addressing both supplier se-lection and supplier development in the same model, together with explicit sustainability components, can prove beneficial to both practitioners and researchers by opening up opportunities for in-sights into practice and theory as well as additional research directions.

2.3 The Case for Flexible Solution Sets

From an analytical viewpoint, the purpose of most mathematical programming models is the identification of an optimal solution. While optimality is important, there are scenarios where it may be advantageous to consider multiple solutions, and particularly if they are diverse, i.e., offering greater heterogeneity in the solution set, without compromising on quality. However, even among a portfolio of optimal or near-optimal solutions, the elements composing a solution vector may still be relatively homogenous with little variation.

Increased diversity among a set of high-quality solutions is valuable for a number of reasons. First, most mathematical programming models are abstractions of reality and necessarily leave out important factors that humans may consider relevant in making decisions (Sharda et al., 1988; Hoch and Schkade, 1996; Williams, 1999; Laguna et al., 2014; Schittekat and Sorensen, 2009). As an illustration, assume a project manager with a limited budget is allocating capital to projects. This manager may be interested in examining dissimilar solutions with respect to risk exposure, but may only have a general idea of what risks may be entailed in any one solution. Or, consider an "optimal" schedule generated for a human resources manager. A small set of high-quality yet diverse schedules could be useful for the inevitable impromptu, real-time adjustments that must be made. Finally, consider a group of decision makers with differing perspectives that cannot explicitly be modelled or even expressed. Given several feasible and useful options, these decision makers could potentially select the most appropriate solution according to their expertise and/or requirements. These are just three of many examples in which great value could be realized in having a readily available set of solutions that are both high-quality and yet mutually diverse.

Provided the number is manageable, multiple high-quality and diverse solutions are of greater value to a decision maker than a single solution, as they offer increased flexibility in the decision making process. Having several diverse solutions that perform relatively well (of high quality) can provide insight into features and inherent trade-offs in the solution space, enabling management to discover key factors in the problem environment. Additional situations where the flexibility of solutions has value for managerial decision makers include time-sensitive, cost-sensitive, or critical one-time decision settings (Takriti et al., 1996; Fagerholt et al., 2009).

In the context of supplier selection and development, consider a decision vector that optimizes the performance metric (e.g., cost, reliability, sustainability rating) subject to certain capacity, time, quality, and other constraints. Additionally, consider two additional decision vectors, both of which score highly in terms of objective function quality e i.e., optimal, or nearly so. Now, all three decision vectors are feasible, that is, they satisfy capacity requirements, quality expectations, and all the other constraints. However, it may be that one of the latter is actually preferable to the original solution vector, as while all three exhibit optimal or near optimal performance, there may be some qualitative and hard to measure features present in the original solution vector that are actually undesirable.

The identification of high-quality yet diverse solutions offers a number of practical benefits for supply chain decisions. Using such solution sets can aid decision makers in various supply chain management 'life cycle' phases (e.g. pre-selection, selection, and post-selection of supplier phases). In the early selection phases, a set of high-quality and diverse solutions will help to filter a larger set of potential suppliers to a more manageable population of key suppliers who can then be invited for bids or requests for proposals. The management of portfolios such as these is an important aspect of strategic management of suppliers (Zhu et al., 2010; Caniels and Gelderman, 2007).

A set of high-quality and diverse solutions can also be used to help with negotiation strategy. Negotiating can become more effective when organizations understand which suppliers are key. In this situation key suppliers would be those suppliers that may frequently appear in the portfolio of potential solutions (i.e., solution set). Managers would then be able to prioritize and categorize groups of suppliers into various levels of importance based on this measure.

Finally, a set of high-quality and diverse solutions may prove valuable in post-selection processes where the most important (strategic) suppliers are identified and used to build capacity, which is also true in sustainability contexts (Ciliberti et al., 2008). Organizations may maintain or strengthen the relationship by offering these strategic suppliers long-term contracts and developmental funding (Lambert and Cooper, 2000). For existing sets of suppliers, organizations may also seek to adjust a given portfolio by reclassifying suppliers.

3 Mathematical Model and Methodology

We now introduce a mathematical model that represents many of the key decisions inherent to the simultaneous selection and development of suppliers. The purpose of the model is to identify an assignment of suppliers to both components and in concert, products that are comprised of such individual components (see Fig. 2 for a visual illustration), that maximizes a supplier sustain-ability performance rating, while simultaneously satisfying supply-chain-related constraints including the important dimension of sustainable supplier development.

3.1 Sustainable Supplier Selection and Development Problem Formulation

We formulate the Sustainable Supplier Selection and Development Problem in the following fashion. Assume that there is a set $\mathcal{S}$ of suppliers to provide a set $\mathcal{J}$ of components, some of which are used to manufacture a set $\mathcal{K}$ of new products. Define:

$$x_{sj} = \begin{cases} 1 & if\ supplier\ s\ is\ selected\ to\ supply\ component\ j\ ; \\ 0 & otherwise, and \end{cases} \tag{1}$$

$$y_{sk} = \begin{cases} 1 & if\ supplier\ s\ is\ selected\ as\ a\ supplier\ of\ product\ k\ ; \\ 0 & otherwise. \end{cases} \tag{2}$$

Let constant $a_{sj} = 1$ if supplier s is capable of supplying component j, and 0 otherwise. Then the following constraints ensure that only those suppliers s that are capable of supplying component j may be selected:

$$x_{sj} \leq a_{sj}\ \forall\ s \in \mathcal{S}, j \in \mathcal{J}. \tag{3}$$

Realistically, there is risk in having too few or too many suppliers, as these conditions can lead to overly fragile or overly saturated supply chains. Thus, the following constraints ensure that minimum (L_j) and maximum (U_j) number of suppliers are satisfied for each component $j \in \mathcal{J}$:

$$L_j \leq \sum_{s \in \mathcal{S}} x_{sj} \leq U_j\ \forall\ j \in \mathcal{J}. \tag{4}$$

It is assumed that each product requires at least one component, though they typically have multiple components. So, let $e_{jk} = 1$ if component j is an element of product k, and $e_{jk} = 0$ otherwise. If component j is an element of product k, then supplier s can only supply component j if supplier s is simultaneously selected as a supplier for product k:

$$e_{jk} x_{sj} \leq y_{sk}\ \forall\ s \in \mathcal{S}, j \in \mathcal{J}, k \in \mathcal{K}. \tag{5}$$

At the same time, a supplier should only be considered as supplying a product k if it also supplies a component j that exists in that product. That is, a supplier cannot supply product k if it does not supply at least one of the components j in that product:

$$\sum_{j\in\mathcal{J}} e_{jk}x_{sj} \geq y_{sk} \ \forall\ s \in \mathcal{S}, k \in \mathcal{K}. \tag{6}$$

Similar to supplier-component uncertainties, there may be risk in having too few or too many suppliers for a given product. Hence, the number of suppliers for each product k is constrained between a minimum number M_k and a maximum number N_k:

$$M_k \leq \sum_{s\in\mathcal{S}} y_{sk} \leq N_k \ \forall\ k \in \mathcal{K}. \tag{7}$$

For every component $j \in \mathcal{J}$, we assume there is some minimum capacity that must be met (collectively) by the suppliers. Assume each supplier $s \in \mathcal{S}$ can supply a quantity of c_{sj} units for each component $j \in \mathcal{J}$. The following constraint ensures that, collectively, the minimum capacity of component j used across all products $k \in \mathcal{K}$ is met by the selected suppliers, where C_{jk} is the minimum required capacity of component j in product k:

$$\sum_{s\in\mathcal{S}} c_{sj}x_{sj} \geq \sum_{k\in\mathcal{K}} C_{jk} \ \forall\ j \in \mathcal{J}. \tag{8}$$

Our model also takes into account supplier development in the form of training activities under budgetary constraints for both components and products. Under a component training budget B_c, where any selected supplier would be required to have environmental/sustainability training on a certain type of component $\bar{j}$ (e.g., toxicity substitution identification, eco-design evaluation, new equipment introduction and operation) at a cost $b_{s\bar{j}c}$, we have:

$$\sum_{s\in\mathcal{S}} b_{s\bar{j}c}x_{s\bar{j}} \leq B_c. \tag{9}$$

Similarly, under a product training budget B_p, where any chosen supplier would be required to have environmental/sustainability training on a certain product $\bar{k}$ at a cost $b_{s\bar{k}p}$, we can write:

$$\sum_{s \in \mathcal{S}} b_{s\bar{k}p} y_{s\bar{k}} \le B_p. \tag{10}$$

Finally, we allow for discretionary judgments for every component j based on organizational limits for unit cost, delivery time, and quality (Feng et al. 2011). We allow for an upper limit π_j on component unit cost p_{sj} for each supplier s and component j:

$$p_{sj} x_{sj} \le \pi_j \ \forall \ s \in \mathcal{S}, j \in \mathcal{J}, \tag{11}$$

an upper limit τ_j on the average delivery time t_{sj} for each supplier s and component j:

$$t_{sj} x_{sj} \le \tau_j \ \forall \ s \in \mathcal{S}, j \in \mathcal{J}, \tag{12}$$

and a lower limit κ_j on the quality q_{sj} for each supplier s and component j:

$$(q_{sj} - \kappa_j) x_{sj} \ge 0 \ \forall \ s \in \mathcal{S}, j \in \mathcal{J}. \tag{13}$$

Collectively, constraints (11), (12), and (13) only allow a supplier s to supply component j if they cay satisfy cost, time, and quality criteria. Among the many possible combinations of suppliers for various components and products, we wish to identify those that satisfy constraints (3) – (13) while optimizing for a (cumulative) sustainability performance rating r_{sj} obtained from choosing supplier s for component j, where higher scores correspond to higher sustainability ratings:

$$max \ \ z = \sum_{s \in \mathcal{S}} \sum_{j \in \mathcal{J}} r_{sj} x_{sj}. \tag{14}$$

Implicit in (14) is the assumption that organizations are capable of evaluating suppliers' sustainability of components and materials to arrive at the sustainability performance ratings, for example using auditing or eco-design criteria (see Hervani et al., 2005; Taticchi et al., 2013) or developing industry specific indices (e.g. Azevedo et al., 2013). We refer to the binary integer program formulated in (1) through (14) as (SSD).

It should be noted that, although sustainability has entered the lexicon of business, its definition and measurement is still in its elementary stages. Maturity matrices for sustainability, especially environmental sustainability, have existed right from the late 1980's and 1990's. Early efforts into environmental sustainability measurement in organizations revolved around total quality environmental management (TQEM) practices and continuous improvement (Wever, 1996). Organizations such as Eastman Kodak sought and developed a ten-point maturity matrix for environmental sustainability (Wever and Vorhauer, 1993; Lave et al., 1997). As the field evolved, environmental sustainability metrics and measures were developed for eco-design, such as those for Herman Miller (Lee and Bony, 2008) and environmental management accounting systems such as those by Polaroid (Sarkis, 2001), each having similar maturity performance measures. Thus, organizations have had numerous operational and control reasons for implementing sustainability performance measures.

Although environmental sustainability has been relatively well established in the literature, social sustainability performance and evaluation lags (Hubbard, 2009; Searcy, 2012; Seuring and Müller, 2008). Primers on broader ‘triple-bottom-line’ sustainability performance evaluation from a research and practical perspective are becoming more prevalent (e.g. Epstein and Buhovac, 2014; Varsei et al., 2014). Increasing adoption of these performance measurement systems integrated with traditional methodological tools such as the balanced scorecard (Butler et al., 2011; Chalmeta and Palomero, 2011) and the analytical hierarchy process (AHP) (Singh et al., 2007; Govindan et al., 2013a, b), sustainability performance ratings will make them more accessible to organizations. Although we do not explicitly recommend or utilize any of these tools and the many specific and general metrics available for sustainability, their existence in the literature and practice exemplifies the applicability of the objective function. Sustainability measures usage for suppliers and supply chain management has garnered substantial and current support (e.g. Bai et al., 2012; Dai and Blackhurst, 2012). In fact, their integration within optimization objective functions itself can prove to be a fruitful research direction.

3.2 Methodology

A single instance of the (SSD) model can be solved using an optimization solver such as CPLEX (IBM ILOG CPLEX, 2013) or Gurobi (Gurobi Optimization 2013). Identifying multiple solutions of high quality, that are simultaneously diverse, is a different question that we answer using the methodology outlined in this paper. Having a portfolio of such solutions enables greater flexibility in managerial decision making. Given the many uncertain and dynamic factors that play into sustainable supplier selection and development decisions, having this information empowers decision makers to consider other factors and motivations that were not explicitly modeled. Such flexibility is absent when considering only a single solution, i.e., the standard output of an optimization solver. Thus, we pursue the identification of high-quality and yet diverse solutions to (SSD).

The diversity of any two binary vectors of identical length, including those that arise as solutions to binary integer programs such as (SSD), can be seen as the sum of the number of vector indices whose values are not in agreement. Thus the diversity of vector A = [1 0 1 0] from vector B = [1 0 0 1] is 2. This definition can be expressed using the Hamming distance or L_1 (taxicab) norm, and has natural extensions when considering diversity with respect to two or more binary vectors, which will be discussed shortly.

While clearly desirable, solutions that are both diverse and of high quality can be challenging to identify. Solutions of relatively high quality tend to evaluate poorly with respect to diversity, due to the structural similarities they share. On the other hand, solutions that score rather high in diversity are likely to be from a remote area of feasible region, and so they may not have an objective function evaluation of high quality. This situation produces tension when both high quality and diversity are emphasized.

We briefly outline the methodology and subsequently discuss its implementation with respect to the supplier selection and development model presented in Section 3.1. For further details on the methodology, we refer to Trapp and Konrad (2013). For ease of reference, let us denote with S the set of constraints (3) -(13) together with the variable space (1) -(2). For the sake of exposition, assume (SSD) has a feasible solution, and further assume that we have an optimal solution vector $x^* = (x^*_{sj}, y^*_{sk}\ \forall\ s \in \mathcal{S}, j \in \mathcal{J}, k \in \mathcal{K})$ and optimal objective function value z^*. This solution can be obtained, for example, from directly solving the formulation in Section 3.1 using an optimization package such as CPLEX (IBM ILOG CPLEX 2013) or Gurobi (Gurobi Optimization 2013). Let X be the set containing all identified solutions, i.e., $X = \{x^*\}$. Given this x^* and z^*, consider the same feasible region but now using the following modified (fractional) objective:

$$R(x) = \frac{N(x)}{D(x)} = \frac{Relative\ Solution\ Diversity}{Relative\ Deterioration\ in\ Objective\ Quality}. \tag{15}$$

Objective (15) expresses the ratio of the relative solution diversity to the relative deterioration in objective function quality (i.e., collective sustainability rating). Now assume we have any other feasible solution $x \in \{0,1\}^n$. The denominator representing the deterioration in objective quality can be obtained using:

$$z^* - \left(\sum_{s\in\mathcal{S}} \sum_{j\in\mathcal{J}} r_{sj}x_{sj}\right). \tag{16}$$

Similarly, the diversity of x with respect to the elements of X can be represented using one of two distinct diversity metrics that are more fully developed as follows.

A set X of high-quality and diverse solutions, say a total of P (assuming there are that multiple distinct feasible solutions in S), can be constructed in an iterative manner. We modify the objective of (SSD) with fractional objective (15), and refer to the resulting formulation as (SSD_M). Although fractional objective (15) is nonlinear, Dinkelbach's algorithm (Dinkelbach, 1967) can be used to find an optimal solution to this type of nonlinear fractional bi-nary integer program. It does so by solving a sequence of linearized problems that are related to the original nonlinear fractional programming problem. So starting with the single element $x^{ð0Þ*}$ ¼ x^* in X, we can add the following binary exclusion constraint to (SSD_M) to ensure that it is not revisited (Balas and Jeroslow, 1972):

$$\sum_{i:x_i^*=0} x_i + \sum_{i:x_i^*=1} (1 - x_i) \geq 1. \tag{17}$$

Then, solving (SSD_M) will generate a solution $x^{(1)^*}$ that maximizes the ratio in (15), i.e., it simultaneously emphasizes solution quality and diversity (with respect to all elements in X).

Consider a sequential process of finding alternate solutions for some iteration $h > 1$. One way to measure diversity is to compute the distance from the centroid of all solutions in X. The centroid is the vector composed of the component-wise average of each element:

$$\boldsymbol{c} = \left(\boldsymbol{c}_i = \frac{1}{h}\sum_{j=0}^{h-1} x_i^{(j)^*}\right). \tag{18}$$

Then the *centroid diversity metric* computes the distance of any vector $x \in \{0,1\}^n$ from the elements of X in the following fashion:

$$\sum_{i=1}^{n} \boldsymbol{c}_i + \sum_{i=1}^{n}(1 - 2\boldsymbol{c}_i)x_i. \tag{19}$$

Alternatively, another way to represent diversity is to compute the minimum distance from any vector $x \in \{0,1\}^n$ to any element in X, represented as:

$$\min_{\{j=0,\ldots,h-1\}} \left\{\sum_{i:x_i^{(j)^*}=0} x_i + \sum_{i:x_i^{(j)^*}=1}(1 - x_i)\right\}. \tag{20}$$

Like the *centroid diversity metric* (19), it is desirable to maximize (20), and so (20) is further referred to as the *maxmin diversity metric*. Additional information on these metrics, as well as an implementation of Dinkelbach's algorithm, are contained in Trapp and Konrad (2013), which also discusses important technical details on normalizing the numerator and denominator to eliminate any predisposed bias in magnitudes.

This entire process can be repeated as often as desired to generate a solution set X, as long as there remain feasible solutions. An overview of this process is depicted in Figure 1.

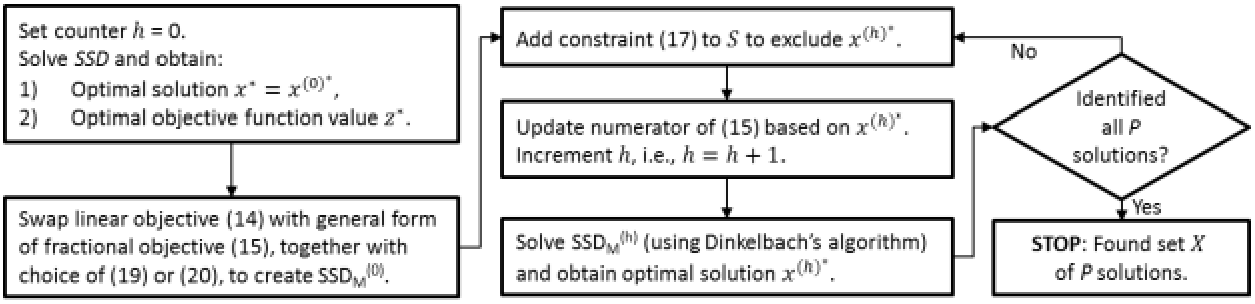

Figure 1: Illustration of algorithm to find *P* diverse and high-quality solutions to (SSD) (Trapp and Konrad, 2013)

3.3 Evaluating Collective Diversity

The collective diversity of the solutions in X can be computed in a manner similar to that used in related studies (Danna and Woodruff 2009, also Prokopyev et al. 2009):

$$D_{bin}(X) = \frac{2}{n|X|(|X|-1)} \sum_{i=1}^{n} \sum_{j=1}^{|X|-1} \sum_{h=j+1}^{|X|} \left| x_i^{(j)*} - x_i^{(h)*} \right|. \tag{21}$$

Thus, given a solution set X, the $D_{bin}(X)$ metric provides the average pairwise distance between solutions, taking a value between 0 and 1.

4 Illustrative Example

We now introduce a small example to illustrate the supplier selection and development model together with the approach to identify high-quality yet diverse solutions. In this minimal working example there are $|\mathcal{S}| = 4$ suppliers, $|\mathcal{J}| = 3$ components, and $|\mathcal{K}| = 2$ products. The considered network is depicted in Figure 2.

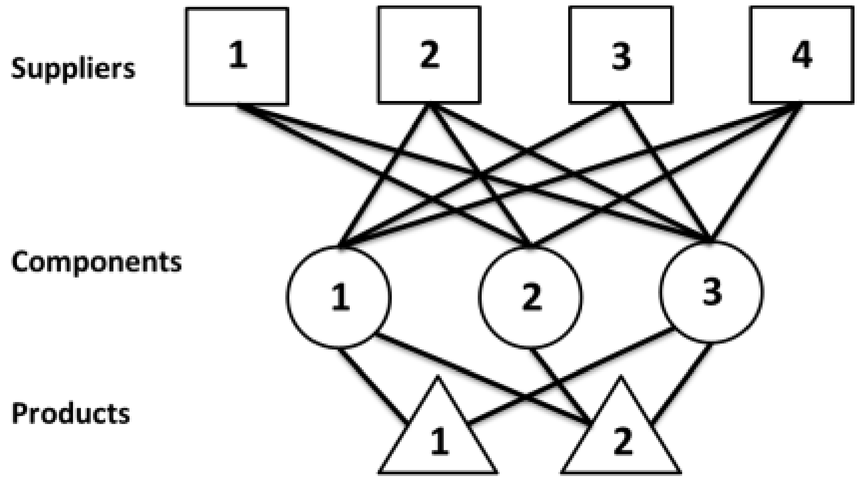

Figure 2: Illustrative example depicting all existing connections via values a_{sj} and E_{jk}

In this example there is a single component training budget (for component $\bar{j}$), and a single product training budget (for product $\bar{k}$). Moreover, there are at least one and at most two suppliers for every component j, and at least one and at most three suppliers for every product k. Cost, time, and quality factors occasionally restrict certain supplier-component combinations (not depicted in Figure 2). Tables 1, 2, and 3 contain representative data for the network such as network interconnectivity values a_{sj} and E_{jk}, sustainability performance ratings r_{sj}, component capacities c_{sj} per supplier, budgetary information on the cost of bringing potential suppliers up to acceptable sustainability levels through sustainability oriented trainings on components or products, etc.

Table 1: Illustrative example values of a_{sj}, r_{sj}, and c_{sj} for all values of supplier s and component j

	a_{sj} values			r_{sj} ratings			c_{sj} values		
Supplier s \ Component j	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
1	0	1	1	*N/A*	2	5	*N/A*	399	715
2	1	1	1	1	3	4	955	365	706
3	1	0	1	2	*N/A*	3	1,018	*N/A*	794
4	1	1	1	4	5	4	785	485	543

Table 2: Illustrative example values of E_{jk} and C_{jk} for all values of component j and product k

	E_{jk} values		C_{jk} capacities	
Component j \ Product k	**1**	**2**	**1**	**2**
1	1	1	566	543
2	0	1	N/A	324
3	1	1	712	362

Table 3: Illustrative example values of training budget costs over all suppliers s for component $\bar{j} = 3$, product $\bar{k} = 1$

	Supplier				
	1	**2**	**3**	**4**	**Budget B_c**
Training budget costs $b_{s\bar{j}}$	11,839	9,618	8,860	10,217	28,000
Training budget costs $b_{s\bar{k}}$	8,881	8,069	9,973	8,579	28,000

Figure 3 depicts the unique optimal solution x^*, where double-weighted connections illustrate the supplier-component (x_{sj}) and supplier-product (y_{sk}) choices.

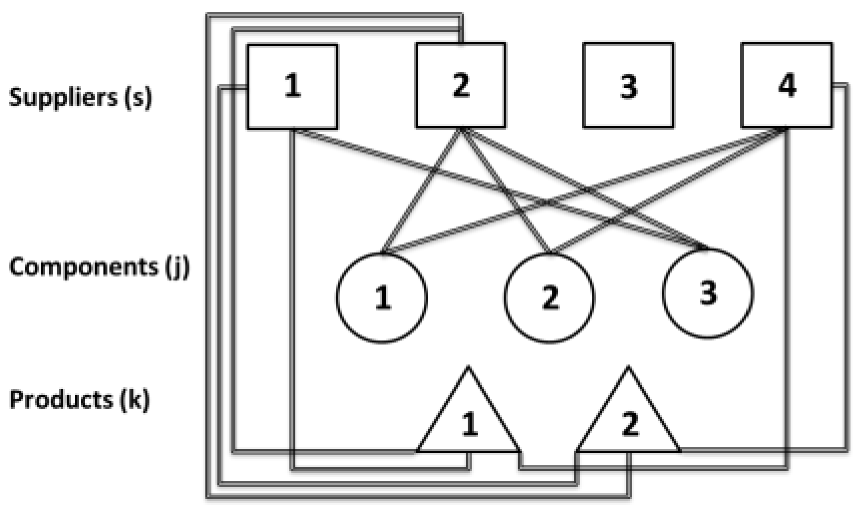

Figure 3: Graphic depicting optimal solution x^* with $z^* = 22$.

For this particular example, x^* has $x^*_{13} = x^*_{21} = x^*_{22} = x^*_{23} = x^*_{41} = x^*_{42} = 1$, $y^*_{11} = y^*_{12} = y^*_{21} = y^*_{22} = y^*_{41} = y^*_{42} = 1$, and all other variables equal to 0. The optimal objective function value corresponding to x^* is $z^* = 22$.

Practically, this solution states that supplier 1 is selected to supply component 3 for products 1 and 2, whereas, Supplier 3 is not selected to supply any components for any products. Similar observations can be made for the other two suppliers. Although the first supplier has the highest sustainability training costs ($11,839) for being brought up to an acceptable level on component 3, at the same time selecting this supplier-component connection also led to a high sustainability performance rating contribution of 5 in the objective function. In all, the focal company (buyer) stayed within budget while maximizing the aggregate sustainability performance rating.

The algorithm described in Section 3.2 can now be carried out to find a single solution that is of high quality and yet diverse from x^*. To begin, an exclusion constraint (17) is added to forbid the algorithm from subsequently returning x^*. While either metric (19) or (20) can be chosen to represent diversity, in this example the centroid metric (19) is used in the numerator of objective function (15). Because $h = 1$, there is a single element x^* in X, and so the centroid metric (19) with respect to x^* can be expressed as:

$$\sum_{i=1}^{n} \boldsymbol{c}_i + \sum_{i=1}^{n}(1 - 2\boldsymbol{c}_i)x_i = x_{11} + x_{12} + (1 - x_{13}) + (1 - x_{21}) + (1 - x_{22}) + (1 - x_{23}) + x_{31} + x_{32} + x_{33} + (1 - x_{41}) + (1 - x_{42}) + x_{43} + (1 - y_{11}) + (1 - y_{12}) + (1 - y_{21}) + (1 - y_{22}) + y_{31} + y_{32} + (1 - y_{41}) + (1 - y_{42}). \quad (22)$$

Using the centroid metric in the numerator of (15), upon completion the algorithm seeks to simultaneously maximize the ratio of diversity to loss in objective quality, and returns an alternate solution $x^{(1)}$ of high quality ($z^{(1)} = 21$) that is simultaneously diverse from x^*. It is depicted in Figure 4. This figure shows that there is a major shift in supplier selection from supplier 2 in the optimal solution, to supplier 3 in this high-quality and yet diverse solution. Supplier 1 remains in the solution and is selected to supply an additional component (component 2) when compared to the optimal solution.

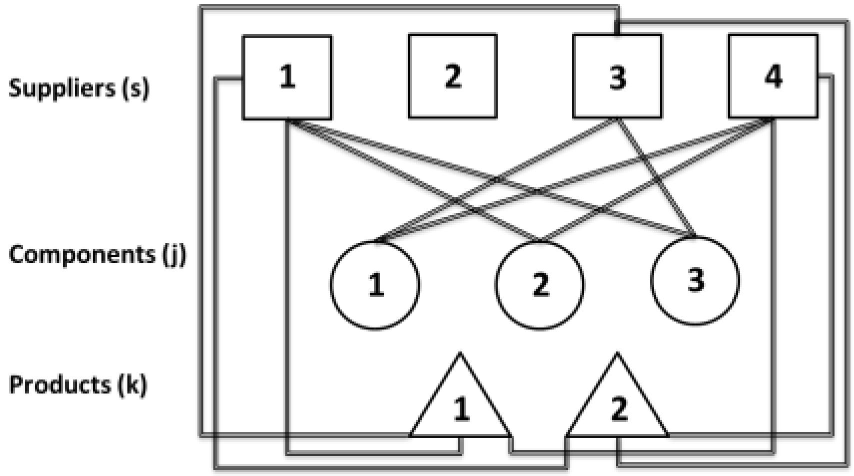

Figure 4: Graphic depicting solution $x^{(1)}$ with high quality ($z^{(1)} = 21$) and yet diverse from x^{*}.

The solution $x^{(1)}$ has $x_{12}^{1} = x_{13}^{1} = x_{31}^{1} = x_{33}^{1} = x_{41}^{1} = x_{42}^{1} = 1$, $y_{11}^{1} = y_{12}^{1} = y_{31}^{1} = y_{32}^{1} = y_{41}^{1} = y_{42}^{1} = 1$, and all other variables equal to 0. It can be seen that, according to expression (22), the centroid diversity metric evaluates to 10 for $x^{(1)}$, which represents a 50% diversity in the solution vector elements. Indeed, because there are only two elements in X, this is also the value of $D_{bin}(X)$, the collective diversity in X. The computation is as follows:

$$D_{bin}(X) = \frac{2}{20 \cdot 2 \cdot 1} \sum_{i=1}^{20} \sum_{j=1}^{1} \sum_{h=j+1}^{2} \left| x_i^{(j)*} - x_i^{(h)*} \right| = \frac{1}{20} \sum_{i=1}^{20} \left| x_i^{*} - x_i^{(1)} \right|. \quad (23)$$

It is equally important to understand what the algorithm did not choose for this initial alternate solution. In particular, it did not choose solution $x^{(2)}$, depicted in Figure 5, which has high quality ($z^{(2)} = 21$) but has lower diversity from x^{*} -- only 10% as expressed using (22).

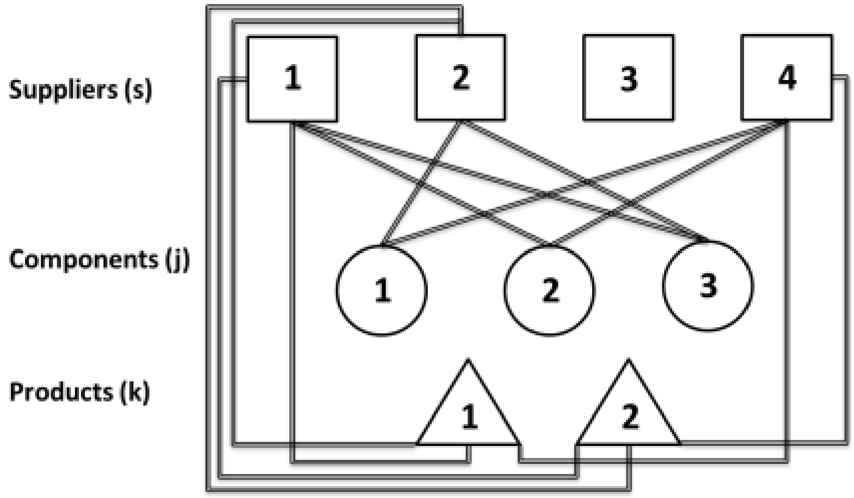

Figure 5: Graphic depicting high-quality solution $x^{(2)}$ ($z^{(2)} = 21$) and yet not diverse from x^*.

Moreover, the algorithm avoided choosing solution $x^{(3)}$, depicted in Figure 6, which scores rather high in diversity – 50% as expressed using (22) – but is somewhat lacking in objective function quality ($z^{(3)} = 16$).

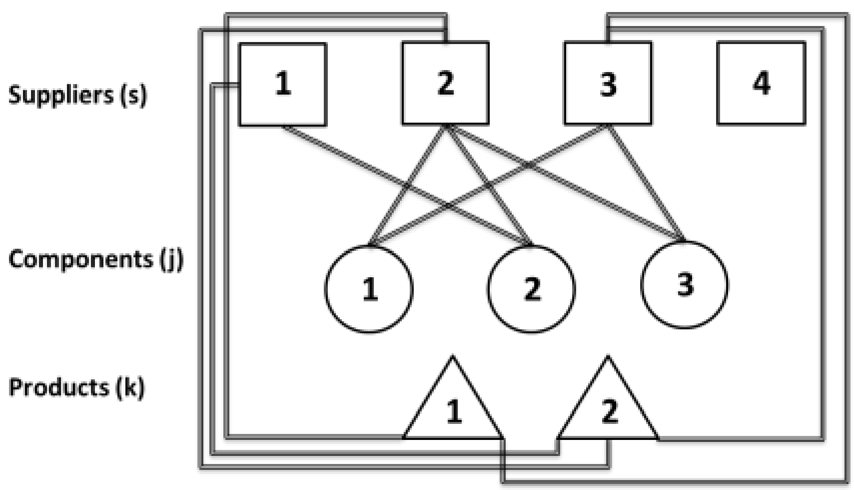

Figure 6: Graphic depicting solution $x^{(3)}$ that is diverse from x^* but not having high quality ($z^{(3)} = 16$).

After this initial iteration, a single constraint in the form of (17) is added to restrict solution $x^{(1)}$ from reoccurring:

$$\sum_{i=1}^{n} \boldsymbol{c}_i + \sum_{i=1}^{n}(1 - 2\boldsymbol{c}_i)x_i = x_{11} + x_{12} + (1 - x_{13}) + (1 - x_{21}) + (1 - x_{22}) + (1 - x_{23}) + x_{31} + x_{32} + x_{33} + (1 - x_{41}) + (1 - x_{42}) + x_{43} + (1 - y_{11}) + (1 - y_{12}) + (1 - y_{21}) + (1 - y_{22}) + y_{31} + y_{32} + (1 - y_{41}) + (1 - y_{42}) \geq 1,$$

the objective function is updated to account for $x^{(1)}$, and the process repeated until a satisfactory number of solutions are obtained.

5 Computational Experiments

To understand the broader behavior of the formulation and methodology, additional runs under various scenarios were considered. The computational performance of the methodology on (SSD) over selected parametric variations is subsequently discussed.

5.1 Computational Setup

Five classes of test instances for the Sustainable Supplier Selection and Development Problem are considered. These classes were constructed using the values for $|\mathcal{S}|$ (number of suppliers), $|\mathcal{J}|$ (number of components), and $|\mathcal{K}|$ (number of products) as indicated in Table 4, where m represents the largest number of rows occurring for any instance of a given class, and n represents the number of columns. For each of the five test classes depicted in Table 4, we generated 25 individual test instances, leading to 125 total test instances.

Table 4: Problem dimensions for considered (SSD) test instance classes

Test class	$\lvert\mathcal{S}\rvert$	$\lvert\mathcal{J}\rvert$	$\lvert\mathcal{K}\rvert$	m	n
1	5	4	3	175	35
2	10	8	6	828	140
3	15	12	9	2,216	315
4	20	16	12	4,574	560
5	25	20	15	8,092	875

The test classes range in size from 5 suppliers, 4 components, and 3 products, up to 25 suppliers, 20 components, and 15 products. These classes are what moderate-to medium-sized companies might realistically consider for selecting and developing strategic relationships with suppliers, and further point to what might be the case for somewhat larger classes.

5.2 Computational Environment

Our approach was coded in Cþþ and compiled using gþþ version 4.4.6 20110731 (Red Hat 4.4.6-3) on a Dell R610 server with 2 Intel Xeon X5690 CPUs each with 6 cores running at 3.47 GHZ and 48 GB. All optimization was performed using the callable library of IBM ILOG CPLEX 12.5 (IBM ILOG CPLEX, 2014). A one-hour limit was set for solving any binary integer program, and numerical stability was prioritized with the CPX_NUMERICAL_EMPHASIS parameter set to CPX_ON. This was done mainly to ensure any potential dis-crepancies of magnitude in the numerator to denominator ratios for our objective were reconciled. While any reasonable value of P solutions could be chosen, for each instance the algorithm was set to retrieve ten solutions**.**

5.3 Computational Results

The computational findings are now presented and discussed.

5.3.1 Summary Results

A full set of ten diverse and high-quality solutions are identified in 96 of the original 125 instances. For four additional instances, less than ten feasible solutions identified – precisely nine, eight, and four (twice). Thus, 25 of the original 125 instances were infeasible, with the majority of these arising in the smallest test class. It is believed this had to do with limited flexibility concerning the number of relationships among suppliers, components, and products. Table 5 details summary performance metrics; sample standard deviations are in parentheses.

Table 5: Summary performance metrics for (SSD) test instance classes

Test class: $\|\mathcal{S}\|/\|\mathcal{J}\|/\|\mathcal{K}\|$	Count of $\|X\|$=10	Mean Iterations		Mean Runtime (seconds)		Mean $D_{bin}(X)$	
		centroid	maxmin	centroid	maxmin	centroid	maxmin
5/4/3	5	1.9 (0.1)	2.2 (0.3)	56.5 (68.0)	114.5 (97.9)	0.17 (0.06)	0.16 (0.09)
10/8/6	22	2.3 (0.2)	3.4 (0.4)	150.6 (56.6)	255.6 (63.8)	0.10 (0.03)	0.17 (0.05)
15/12/9	24	2.4 (0.2)	4.2 (0.6)	170.7 (46.6)	348.3 (37.5)	0.08 (0.03)	0.13 (0.02)
20/16/12	22	2.6 (0.2)	4.7 (0.7)	317.3 (71.0)	456.0 (111.4)	0.06 (0.02)	0.10 (0.02)
25/20/15	23	2.5 (0.1)	4.9 (0.8)	392.8 (169.0)	577.2 (213.5)	0.05 (0.02)	0.11 (0.02)

Unless otherwise specified, in what follows the analysis considers the 96 test instances for which a full set of ten diverse and high-quality solutions were identified.

5.3.2 Algorithmic Analyis

In all five test classes, the algorithmic runtime was relatively modest and well within the time for a strategic decision (i.e. a decision that may impact long-term operations of an organization). The algorithmic runtime for the centroid metric, averaged over all instances, was approximately 223 seconds, while it was 384 seconds for the maxmin metric. The maximum runtime for any solved test instance was 676 seconds for centroid and 918 seconds for maxmin – approximately 15 minutes in the worst case. Additionally, for the smallest test class, the mean runtimes were approximately one minute (65 seconds) for the centroid metric, and under two minutes for the maxmin metric. Even for the largest test class, the mean runtimes were less than ten minutes for both the centroid and maxmin metrics. These runtimes were a direct result of the low iteration counts of the algorithm. The centroid metric typically averaged between two and three iterations, whereas the maxmin metric typically required another two or so iterations to converge, leading to slightly longer runtimes.

6 Discussion on Quality and Diversity of Solutions to (SSD)

We now discuss the algorithmic performance on (SSD) with respect to the quality and diversity of the obtained (SSD) solutions.

6.1 Analysis of Solution Diversity

Over all 96 test instances for which ten high-quality and diverse solutions were found, the maxmin metric produced an average pairwise diversity ($D_{bin}(X)$ value) of 0.1392, whereas the centroid came in with slightly less diverse solution sets, having an average $D_{bin}(X)$ value of 0.0793. The maxmin metric also yielded higher diversity in within the five individual test classes. This greater diversity, however, appears to come at the expense of longer algorithmic runtimes.

Counting the number of "wins" provides another viewpoint: the maxmin metric outperformed the centroid metric on diversity of solution roughly 95% of the time (91 out of 96 instances), whereas the centroid metric outperformed the maxmin metric only 4% of the time (4 out of 96). One test instance yielded the same solution set X and so was a “tie”. Moreover, the maxmin metric wins were often quite convincing in terms of diversity. We also noticed that as the number of suppliers, components, and products increased, that is, from the smallest to the largest test instance classes, there was a clear decreasing trend in the $D_{bin}(X)$ values for both the centroid and the maxmin metrics. We attribute this decreasing trend to the structure of the underlying optimization problem. While the number of binary variables grew, feasible variable combinations increased at a much slower rate, limiting the diversification possibilities.

6.2 Analysis of Solution Quality

To quantify the quality of the identified solutions, we considered all obtained solutions apart from the initial solution (since, by algorithmic construction, it is already an optimal solution). For both diversity metrics and over all instances, the same solution set size was observed in our computational experiments – although it is important to make clear that significantly different solutions were generated within these sets by the individual metrics. Again, there were 96 instances for a full $|X|$ = 10 solutions were identified, and an additional four instances for which found $|X|$ = 9, $|X|$ = 8, and (2) $|X|$ = 4 feasible solutions, respectively. Removing the initial optimal solutions for these instances yielded 885 alternate solutions for which quality was evaluated.

The quality of any alternate solution x can be quantified by determining its gap from optimality (i.e., distance from the maximum objective function value). Numerically, this can be expressed in the following fashion, where ϵ is a very small positive number:

$$\frac{z^* - (\sum_{s \in \mathcal{S}} \sum_{j \in \mathcal{J}} r_{sj} x_{sj}) + \epsilon}{z^* + \epsilon}. \tag{25}$$

The average gap from optimality for alternate solutions generated by the centroid metric was 1.51%, and slightly higher for the maxmin metric at 3.10%. This result is consistent with the overall trends that the maxmin metric tends to identify alternate solutions with higher diversity – albeit at a slightly higher computational time, *and slightly lower quality*. Table 6 displays the counts and percentages of the quality of these alternate solutions. For instance, the first row depicts the raw counts and percentages (as a whole) of alternate solutions that have gaps from optimality between [0, 0.0001]. For both the centroid and the maxmin metrics, there are 39 (out of 885) alternate solutions having this gap from optimality, or roughly 4%.

Table 6: Representing the quality of obtained alternate solutions for two metrics

Solutions with Gaps Between:		Raw Count		Percentage	
Lower	**Upper**	**Centroid**	**Maxmin**	**Centroid**	**Maxmin**
0	**0.0001**	39	39	4.41%	4.41%
0.0001	**0.01**	581	290	65.65%	32.77%
0.01	**0.05**	202	394	22.82%	44.52%
0.05	**0.10**	39	108	4.41%	12.20%
0.10		24	54	2.71%	6.10%
	Total	885	885	100.00%	100.00%

The quality of the alternate solutions is further demonstrated in the histograms represented in Figures 7 and 8. Both figures illustrate the gap from optimality on the x-axis, and the corresponding count of solutions in the y-axis. Figure 7 illustrates these data for the centroid diversity metric, while Figure 8 pertains to the maxmin diversity metric (note the disproportionality of y-axis scales in the two figures). A large majority of the alternate solutions (over 90% for the centroid metric, and over 80% for the maxmin metric) are within 5% of optimality. However, the metrics differ in that the centroid metric has over 70% of its alternate solutions within 1% of optimality, while the maxmin has just over 37% of the alternate solutions in this category – another indication that the maxmin metric sacrifices some quality for a greater diversity in the solution set.

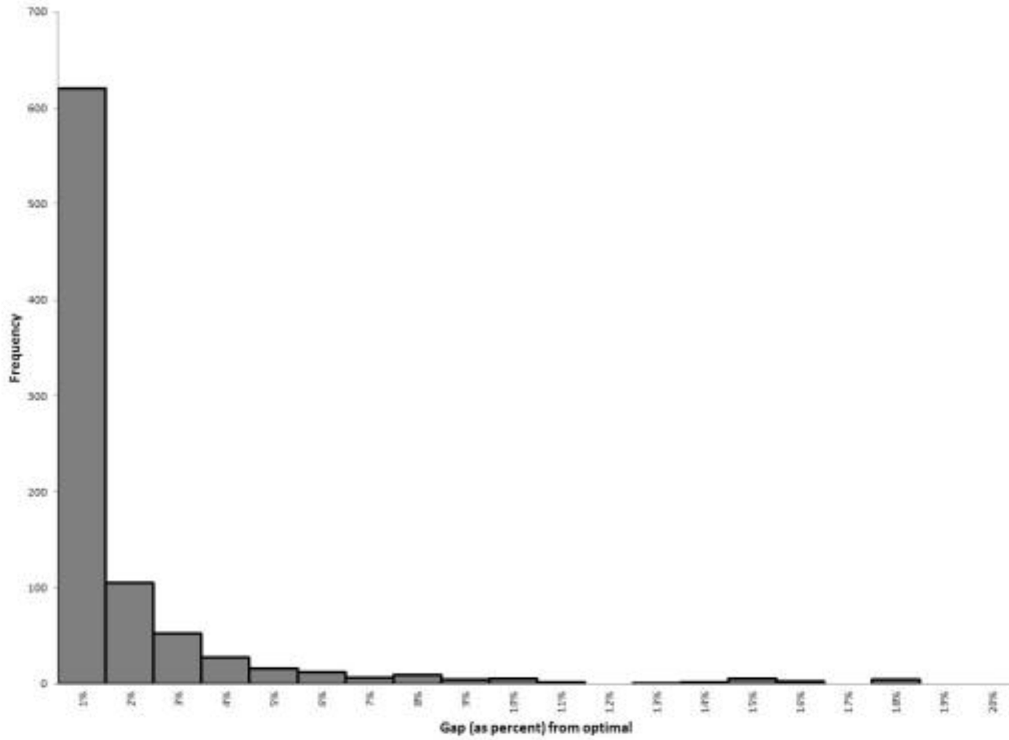

Figure 7: Histogram illustrating quality of alternate solutions for centroid diversity metric

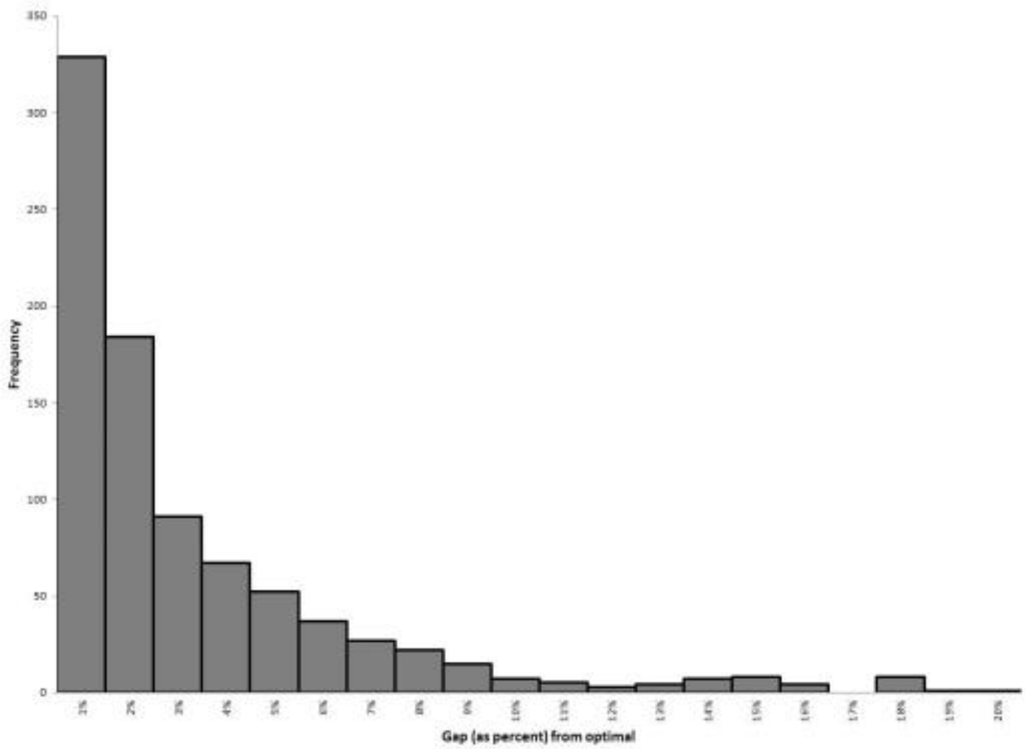

Figure 8: Histogram illustrating quality of alternate solutions for maxmin diversity metric

7 Conclusions

This paper makes two main contributions to the literature. First, it introduces a new optimization model using binary integer programming for simultaneous supplier selection and development, specifically within the environmental sustainability context. The mathematical model addresses the previously disjoint problems of supplier selection and supplier development. The purpose of the model is to identify an optimal choice of supplier-component and supplier-product combinations subject to a number of conventional supply chain restrictions. The model incorporates aspects of sustainability in the form of supplier sustainability ratings that drive the objective function, and budgets for sustainable training activities for both components and products that are assigned to specific suppliers.

Given the increasingly complex decisions inherent in supplier selection and development, especially with sustainability dimensions, the second main contribution of this paper is the demonstration of a recently developed tool (Trapp and Konrad, 2013) to quickly identify high-quality and diverse solutions to this problem class. It illustrates a powerful methodology that can support and enhance managerial, attitudinal, decision-making practices to a wide range of optimization applications (formulated as binary integer linear programs) that include problems in sustainable supply chain management and development. In particular, the optimization tool could prove valuable for sustainable supply chain decision support systems.

Practically, the methodology advances supplier selection models that only focus on levels of criteria and how well suppliers meet these criteria. The model introduced here also explicitly incorporates as a selection criterion the amount of development required for a supplier to achieve an acceptable sustainability level.

The methodology was demonstrated using one of two distinct diversity measures (centroid and maxmin) on a large set of generated test instances. The sizes of test instance classes considered reflect a wide variety of small- to medium-sized supply chain structures. For each test instance, ten solutions were requested.

Over all feasible instances, average runtimes were relatively short (a matter of minutes), average collective diversity was on the order of 10%, and average solution quality was at around 1-2% of optimal (as measured by the gap from optimality). When comparing and contrasting these two metrics, the centroid metric featured shorter runtimes, higher quality, and lower diversity, while the maxmin metric favored solutions with higher diversity but longer runtimes and lower quality. Furthermore, our computational findings when applying this methodology to (SSD) largely reinforce the results of Trapp and Konrad (2013).

There were some limitations to this study, including the use of synthetic test data in lieu of actual supply-chain data. Though the intention was to make this data as real as possible, clearly the study could have been more valuable in a real-world setting, with managers actually utilizing the methodology. Moreover, there are limits to extending the sizes of test instance classes we considered; indeed, if hundreds or even thousands of suppliers, components, and products exist in the same supply chain structure, alternative methods may be necessary for solving the corresponding formulations. We leave such considerations for future studies.

Additionally, the supplier sustainability ratings are subject to closer examination. While they were randomly generated, it is not hard to conceive of obtaining such scores through surveys or other decision modeling approaches such as AHP. Indeed, even rough estimates highlight the power of this decision-support tool as it allows decision makers to explore the decision space of, roughly-speaking, high-quality and yet diverse solutions. This initial research sets the path toward incorporating the tool into a broader methodology and decision support systems that could integrate performance measurement with the evaluation of sustainability in supply chains.

We should also note that other approaches exist to handling the problem of simultaneously identifying high-quality and yet diverse solutions to binary integer programs such as (SSD). One approach is that of Danna and Woodruff (2009) and/or the solution pool of CPLEX (IBM ILOG CPLEX, 2014), though this comes with potential access limitations, for example, commercial uses require a CPLEX license. Our approach, on the other hand, is not proprietary, and can be implemented in conjunction with any solver, including those that are open-source. Still other approaches include multi-objective optimization, metaheuristic approaches, and preemptive optimization; we refer the reader to Trapp and Konrad (2013) for additional discussion.

Future extensions include augmenting the sustainable supplier development measures to include, for example, equipment and technology investments by a focal company in its suppliers. Additionally, it would be interesting to allow for any conducted training initiatives to interact with (i.e., increase) the sustainability performance ratings in the objective function. Finally, another important aspect is that the solution methodology has not as of yet matured to incorporate continuous or general integer variables. Thus, if it is desirable to extend the model to include such variables, the solution methodology is not technically feasible based on the general state-of-the-art. Further investigation would be warranted should modeling of these techniques advance.

8 Acknowledgments

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