A Decision Support System to Evaluate Suppliers in the Context of Global Service Providers

Bruno P. Bruck[1][a], Dario Vezzali[2][b], Manuel Iori[3][c], Carlo Alberto Magni[4][d] and Daniele Pretolani[3]

[1]*Centro de Informática, Universidade Federal da Paraíba, 58058-600 João Pessoa, Brazil*

[2]*"Marco Biagi" Foundation, University of Modena and Reggio Emilia, 41121 Modena, Italy*

[3]*Department of Sciences and Methods for Engineering, University of Modena and Reggio Emilia, 42122 Reggio Emilia, Italy*

[4]*Department of Economics "Marco Biagi", University of Modena and Reggio Emilia, 41121 Modena, Italy*

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Abstract: In this paper, we present a decision support system (DSS) developed for a global service provider (GSP), which solves a real-world supplier selection problem. The GSP operates in the Italian market of facility management, supplying customers with a variety of services. These services are subcontracted to external qualified suppliers spread all over Italy and chosen on the basis of several criteria, such as service quality, availability and proximity. Selecting the best supplier is a complex task due to the large number of suppliers and the great variety of facility management services offered by the GSP. In the proposed DSS, the choice of the best supplier for a certain service is made according to a thorough multi-criteria analysis. The weights for the criteria were generated by implementing both a simplified analytic hierarchy process and a revised Simos' procedure, later validated by the decision makers at the GSP. The DSS provides quick access to historical performance data, visual tools to aid decisions, and a suggested ranked list of suppliers for each given contract. The effectiveness of the proposed system was assessed by means of extensive simulations on a seven-year period of real-data and several rounds of validation with the company.

1 INTRODUCTION

Supplier selection is a well known strategical problem in supply chain management. Many authors agree on the idea that a careful selection of suppliers leads to long-term competitive advantages (Goffin et al., 1997). To perform this careful selection, it might be convenient to adopt a multi-criteria evaluation that takes into account different characteristics of suppliers. According to (Ho et al., 2010), quality, delivery and cost are the most popular criteria, but several other aspects might be as important depending on the context. Grouping and weighting these multiple criteria is not an easy task though, and a careful analysis is usually required to obtain the best results.

Such a careful selection is particularly critical in the facility management industry, where the term Global Service Provider (GSP) is used to identify general players which compete to supply their customers (e.g., banks, hotels, offices or shop chains) with facility management services, by subcontracting their execution to external qualified suppliers. Indeed, the definition of a comprehensive multi-criteria evaluation might be crucial to support GSPs in the selection of the most adequate partners in their business.

Multi-criteria decision analysis (MCDA) is a well-established research field which deals with decision problems, such as ranking and sorting, where the decision process must consider multiple criteria (Ishizaka and Nemery, 2013). In this sense, applying MCDA to the problem of selecting the best supplier for a requested service is of particular interest. As reported by (Ghodsypour and O'Brien, 2001), (Çebi and Bayraktar, 2003) and (Ho et al., 2010), integrated approaches that combine MCDA and other methods,

[a] https://orcid.org/0000-0003-4361-7476
[b] https://orcid.org/0000-0002-3842-6678
[c] https://orcid.org/0000-0003-2097-6572
[d] https://orcid.org/0000-0003-3066-8426

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like optimization and simulation, are to some extent diffused in the literature of supplier selection.

This paper presents a real case study on the implementation of a DSS for a multi-criteria supplier evaluation problem in the facility management industry. In particular, the DSS was developed to support *H2H Facility Solutions S.p.A.*, an Italian GSP based in Zola Predosa (Bologna), in the process of supplier selection. *H2H Facility Solutions S.p.A.*, as a GSP, supplies its customers with a series of facility management services, which can be classified as planned preventive maintenance, corrective maintenance or extraordinary maintenance. The category of services provided might vary from air-conditioning and heating systems maintenance to water supply, electrical systems, elevators, fire protection systems maintenance, cleaning, surveillance, and so forth. The DSS was developed in partnership with the company by carefully defining a comprehensive hierarchical tree of criteria on which supplier evaluation is performed and implementing a simplified Analytic Hierarchy Process (AHP) to compute the weights of identified criteria. In order to formally describe the decision problem that *H2H Facility Solutions S.p.A.* solves each time a facility management service, or long-term maintenance contract, has to be subcontracted, a multi-objective integer programming (IP) model was formulated. The proposed methodology was implemented and integrated in a prototype (i.e., a web application), which was tested with potential users on a real data set obtained both from historical data provided by the company and by collecting additional data from an online survey sent to a sample of suppliers. Following an accurate data preparation process, a ranking of suppliers for each specific service category has been derived by evaluating an aggregated score. Finally, a simulation of supplier selection over a seven-year horizon was performed by combining the implemented multi-criteria evaluation method with a heuristic algorithm derived from the multi-objective IP model. The problem was solved using a weighted sum scalarization method in order to create and compare different scenarios, with the objective of maximizing the average aggregated score of selected suppliers and minimizing the average distance between the facilities of customers and the appointed branches of suppliers to whom the maintenance contract is subcontracted.

The remainder of this paper is structured as follows. Section 2 presents a brief literature review on supplier selection. In Section 3, the supplier selection problem in the context of GSPs is formally defined. The proposed multiple criteria evaluation, the computation of weights using the AHP and the revised Simos' procedure and the detailed comparison of results are provided in Section 4. Section 5 describes the DSS prototype implementation, while the computational experiments are reported in Section 6. Finally, in Section 7, we draw conclusions and formulate possible future research directions.

2 LITERATURE REVIEW

Integrated approaches, optimization and evaluation methods based on multiple criteria for supplier selection have been widely studied since the early 1990s. For relevant seminal works we refer to (Weber et al., 1991), (Goffin et al., 1997), (Ghodsypour and O'Brien, 1998) and (Ghodsypour and O'Brien, 2001). Instead, for a more in-depth overview on this field of research, we refer the interested reader to the recent surveys of (Ho et al., 2010), (Ware et al., 2012) and (Chai et al., 2013). Then, in the latest years, the topic of sustainability is drawing increasing attention even in supply management due to its high applicability. For an overview on the problem of green supplier selection we refer to the survey of (Govindan et al., 2015).

The AHP is a multi-criteria decision method developed in the early 1970s by Thomas Saaty, whose purpose is to break down a decision (e.g., a selection or ranking problem) into factors, arranged in a hierarchic structure from an overall goal to criteria, subcriteria and alternatives in successive levels (Saaty, 1990). The AHP can be applied as an individual method or integrated with other techniques, due to its simplicity, ease of use, and flexibility. Among the multi-criteria decision making approaches for supplier evaluation and selection surveyed by (Ho et al., 2010), integrated AHP approaches were proved to be the most commonly used. In addition, from the very recent survey of (Ho and Ma, 2018) it also emerges that integrations of the AHP were widely applied in manufacturing and logistics areas, whereas the most commonly studied problem is supplier evaluation and selection. The integrated approach that most concern our work is indeed AHP-mathematical programming.

In the following, a more detailed review of a few relevant articles is reported concerning integrated AHP-mathematical programming approaches. The first two papers are taken from a stream of literature between 1997 and 2006, as surveyed by (Ho, 2008); the next two come from a stream of literature between 2007 and 2016, as surveyed by (Ho and Ma, 2018).

In (Çebi and Bayraktar, 2003), an integrated approach which combines AHP and Lexicographic Goal Programming was proposed and applied for a particular supplier selection problem of a Turkish food company. In this case, quality, delivery and cost factors were selected as the objective functions of a mathematical model, while a utility function, expressing supplier scores, was added to the model and derived through an AHP. The AHP considers further criteria not related to quality, delivery and cost, such as logistics, technological capability, business (in terms of reputation, market position, financial strength, and management skills), and relationship (in terms of ability to communicate, past experiences, and competences of sales representatives).

In (Wang et al., 2004), an integrated multi-criteria decision making methodology for supplier selection was developed, which combines AHP and Preemptive Goal Programming (PGP). In particular, the selection of criteria and their arrangement in a hierarchic structure is based on the Supply Chain Operations Reference framework. The PGP model is then used to address some problem constraints, such as the capacity of suppliers, the number of suppliers required, and so on. In this case, the priorities computed using the AHP are inserted in the objective function as coefficients.

In (Kull and Talluri, 2008), an integrated approach for risk reduction in supplier selection, resulting in a combination of AHP and Goal Programming (GP), has been proposed. In particular, the AHP is used to derive risk scores for suppliers, while taking into account product life cycle phases. The so-obtained risk scores are then incorporated in an objective function of a GP model, which considers other constraints, related to lead time, quality, capacity of suppliers, minimum order quantities, and demand satisfaction. The proposed integrated approach was tested at a mid-size second-tier automotive supplier.

In (Mafakheri et al., 2011), an integrated approach for supplier selection and optimal order allocation, combining AHP and Dynamic Programming (DP), was proposed. Firstly, a ranking of suppliers based on four criteria (price performance, quality, delivery performance, and environmental performance), which are further divided into 21 total sub-criteria, is created using the AHP. Then, the information obtained by applying the AHP is passed to a bi-objective DP model, whose goal is to maximize the Total Value of Purchasing, while minimizing the Total Cost of Purchase. The two objective functions are subjected to a series of constraints, related to capacity of suppliers, maximum level of inventory allowed, and demand satisfaction.

Recently, several authors have successfully developed DSSs based on MCDA to help decision makers in selecting the best suppliers. An interesting work that resembles ours is the one by (Dweiri et al., 2016), in which an integrated AHP-based DSS for supplier selection in automotive industry was developed. In this implementation, AHP is applied to rank automotive suppliers in Pakistan, identifying four main criteria (price, quality, delivery and service) from a literature review, and further dividing them into sub-criteria (e.g., lead time, error, and on-time delivery in order to assess delivery; order update, warranty, and geographical location in order to evaluate service). The relative weights of criteria and sub-criteria were computed using an AHP-based on the opinions of sourcing experts, collected through a survey. The DSS was tested on a simplified case study consisting of three suppliers and a sensitivity analysis was performed in order to verify the robustness of the proposed method.

In contrast, our DSS was implemented in the context of GSPs and tested on a broader database consisting of 158 suppliers. The identification of the main criteria, and their relative sub-criteria, was performed in partnership with the company in an early stage of our work. The computation of the weights was performed using AHP and data from a survey performed with experts from the company.

Remarkably, our work provides a series of valuable contributions, as compared to the reviewed literature:

- The choice of criteria and their relative sub-criteria, performed jointly with an extended working group from the company, is consistent with the most popular evaluating criteria found in the literature on supplier selection.
- We use the AHP to compute the weights of a complex and multilevel tree of criteria and, additionally, the obtained results are compared and validated by a revised Simos' procedure (Figueira and Roy, 2002). Our pairwise comparisons are based on a simplified 1-5 scale instead of the fundamental 1-9 scale for AHP preference originally proposed by Saaty, in order to simplify the surveying process that precedes the definition of comparison matrices. Nevertheless, the proposed methodology is highly repeatable and can be reiterated at regular intervals in accordance with the *desiderata* of the company.
- The specific supplier evaluation and selection problem of *H2H Facility Solutions S.p.A.* was formally defined by a multi-objective IP model, in order to consider a set of constraints.
- Our case study is built on a broad database of 158 suppliers, which it makes particularly relevant in terms of problem dimension.
- Extensive simulations on a seven-year period of real-data were performed, in order to recreate and

repeat the choices made by the company, while applying the multi-criteria evaluation.

- Finally, the proposed methodology was implemented and integrated in a DSS prototype (i.e., a web application) which was delivered to the company.

To the best of our knowledge, no analogous strategic and operational tool exists in supplier selection literature. Furthermore, because of the emerging role of GSPs in many different markets, our study constitutes a valuable real-world application of AHP, MCDA and optimization.

3 PROBLEM DEFINITION

In our case study, a facility management contract is related to a service and concerns a particular facility. Every time the GSP formalizes a contract with a customer, the contract is subcontracted to an external qualified supplier that is capable of providing the required service, in accordance with a predefined service-level agreement (SLA). Both the contract and the subcontract demand a negotiation phase, respectively, between the GSP and the customer, and between the GSP and the supplier.

Formally, given a set C of contracts and a set F of suppliers, the supplier selection problem in the context of GSPs is to subcontract a series of facility management contracts to the best suppliers with the dual objective of (i) maximizing the total score of the selected suppliers and (ii) minimizing the total distance. In particular, we define d_{cf} as the geographical distance between the facility to whom contract c is related and the branch of supplier f that is responsible for supplying the facility management service. For each supplier, a score $s_f \in [0,100]$ is obtained by means of the MCDA that is described in the following section. Basically, s_f represents an aggregated adimensional score derived from the tree of criteria. This tree was developed in partnership with the company to serve as the basis for the supplier evaluation procedure. Furthermore, let us define q_f as the capacity in terms of the maximum number of contracts that can be assigned to supplier f. Possible preferences of customers are expressed through a binary parameter p_{cf}, which takes value 1 if supplier f is explicitly required for contract c and 0 otherwise. On the other hand, the potential refusal of a supplier by a customer is expressed through another binary parameter r_{cf}, taking value 1 if contract c cannot be subcontracted to supplier f and 0 otherwise. In addition, we set a maximum acceptable distance α, between the nearest branch of supplier f and the particular facility of customer associated with contract c.

Let x_{cf} be a binary variable that takes value 1 if contract c is subcontracted to supplier f and 0 otherwise, and y_f be a binary variable that takes value 1 if at least one contract is subcontracted to supplier f and 0 otherwise.

The *supplier selection problem* (SSP) is a particular bi-objective version of the generalized assignment problem, which consists of determining the assignment of each contract to a supplier, by satisfying the aforementioned constraints, while maximizing the total score and minimizing the total distance. Indeed, proximity between customers and suppliers is desirable because it should guarantee a better compliance with SLAs and, consequently, a greater customer satisfaction. The SSP can be then modeled as in the following.

$$z(SSP) = \min \left(-\sum_{c \in C} \sum_{f \in F} s_f x_{cf} ; \sum_{c \in C} \sum_{f \in F} d_{cf} x_{cf} \right) \tag{1}$$

subject to

$$\sum_{f \in F} x_{cf} = 1 \qquad \forall\, c \in C \tag{2}$$

$$\sum_{c \in C} x_{cf} \le q_f \qquad \forall\, f \in F \tag{3}$$

$$x_{cf} = 1 \qquad \forall\, c \in C, f \in F : p_{cf} = 1 \tag{4}$$

$$x_{cf} = 0 \qquad \forall\, c \in C, f \in F : d_{cf} > \alpha, r_{cf} = 1 \tag{5}$$

$$x_{cf} \in \{0,1\} \qquad \forall\, c \in C, f \in F. \tag{6}$$

The objective function (1) maximizes the score of the selected suppliers and minimizes the total distance. Constraints (2) impose that each contract c has to be assigned to exactly one supplier, whereas constraints (3) express the capacity of suppliers. According to constraints (4), contract c is assigned to supplier f if the customer expresses its preference for it. On the other hand, according to constraints (5), contract c cannot be assigned to supplier f if the customer expresses its refusal for it or if supplier f is more distant than α. Finally, constraints (6) define the domain of the variables.

The purpose of this formulation is mainly descriptive. However, note that the greedy heuristic algorithm proposed in Section 5 is more advanced because it considers a dynamical aspect of the problem, such as the daily update of score s_f due to the assignment of new contracts to suppliers. Such a dynamical evaluation should avoid the issue of saturating a few suppliers with most of the contracts, which has the potential of gradually deteriorating their performance in the long-term.

4 MULTIPLE CRITERIA EVALUATION

In the previous section, we introduced the score s_f as an aggregated value for each supplier $f \in F$. Recall that the evaluation of this score is a result from an MCDA performed in partnership with the company. This analysis has been conducted through several rounds of interviews, which have led to the definition of a multi-level tree of criteria, on which supplier evaluation is based.

In particular, three levels of criteria were identified. The *macro* criteria directly contribute to define the score s_f for each supplier f. This first level is broken down into a second level of *micro* criteria, which, in a few cases, are further split into a third level of *nano* criteria.

Economic indicators (ECI), technical and professional capability (TPC), additional saturation capacity (ASC), service level performance (SLP), and references (REF) were carefully selected as the *macro* criteria that fully describe the principal dimensions of supplier evaluation in the context of GSPs.

For the sake of conciseness, we only report a deepened explanation of the five *macro* criteria. In detail, ECI aim to give an evaluation of suppliers in terms of dimension and economic soundness, regarding the last year financial statements. TPC evaluates the organizational structure, the competencies and the extensiveness of suppliers over the territory. ASC gives the residual capacity of suppliers in terms of possibility to accept new contracts. SLP aims to deeply evaluate the suppliers on the basis of several dimensions of performance and on their historical data. Finally, REF are particularly important to qualify suppliers, given that they specify the references of customers with whom they have already worked.

In the following, we report the detailed list of *micro* criteria for each of the aforementioned *macro* criteria:

- ECI: revenue (REV) and leverage (LEV);
- TPC: workers per service (WPS), qualifications per worker (QPW), office workers per employee (OPE), revenue per employee (RPE), and number of provinces per branch (PPB);
- ASC: facilities per worker (FPW), square meters per worker (SMW), and revenue produced with *H2H Facility Solutions S.p.A.* per total revenue (RPR);
- SLP: operational punctuality (OPT), administrative punctuality (APT), flexibility (FLX), quality (QLT), internal feedback (IFB), and external feedback (EFB);
- REF: number of references (NRF) and average reference segment (ARS).

These *micro* criteria are very context-specific and, among them, the *micro* criteria regarding SLP are further broken down into a series of *nano* criteria, which are listed in the following:

- OPT: percentage of planned preventive maintenance services performed out of SLA (PPO), percentage of corrective maintenance services performed out of SLA (PCO), percentage of quotes presented late (PQP), and percentage of quotes executed late (PQE);
- APT: percentage of requested documents presented late (PDL), and percentage of maintenance reports erroneously filled out (PRE);
- FLX: ratio of extraordinary maintenance to planned preventive maintenance (REP), percentage of rejected corrective maintenance services (PRS), and assigned but not performed services (NPS);
- QLT: ratio of quoted extraordinary maintenance to extraordinary maintenance (RQE), percentage of accepted quotes (PAQ), percentage of notifications from customers (PNC), percentage of incomplete maintenance services (PIS), percentage of additional information sent by means of the maintenance app (PAI), and percentage of planned preventive maintenance services not performed (PPN);
- IFB: average internal score (AIS), and affordability index (AFI);
- EFB: this *micro* criterion is not further defined.

Figure 1 illustrates the three-level tree of criteria, on which supplier evaluation is based.

Starting from the aforementioned tree of criteria, the score s_f is derived as the sum of the products of weights of criteria and their evaluations, which are first of all normalized in $[0,1]$ and then scaled in the interval $[0,100]$ for better understanding. We provide further details about the normalization process in Section 5.

In particular, by using the *simplified AHP* and the revised Simos' procedure described in Sections 4.1 and 4.2, the weights of criteria are computed as follows:

1. At the *first* level, the weights of *macro* criteria are determined.
2. At the *second* level, for each *macro* criterion, the weights of *micro* criteria are determined.
3. At the *third* level, for each *micro* criterion, the weights of *nano* criteria, if they exist, are determined.

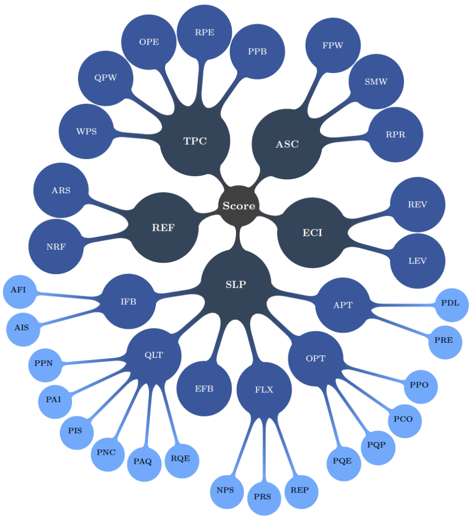

Figure 1: Tree of criteria.

Note that, at each sub-level (i.e., a sub-level might be related to the score s_f or a particular *macro* or *micro* criterion) the sum of the weights should be equal to 1.

The score s_f is then obtained by an iterative *bottom-up* sum of the products of weights and normalized evaluations, where the partial score of each *micro* criterion is determined based on weights and evaluations of its *nano* criteria, if they exist, and the partial score of each *macro* criterion is determined based on weights and evaluations of its *micro* criteria.

At the end of this iterative process, the score s_f is computed as follows:

$$s_f = (p_{IEC}\, s_{IEC}) + (p_{TPC}\, s_{TPC}) + (p_{ASC}\, s_{ASC}) + (p_{SLP}\, s_{SLP}) + (p_{REF}\, s_{REF}) \quad (7)$$

where p_{IEC}, p_{TPC}, p_{ASC}, p_{SLP}, and p_{REF} are the weights of *macro* criteria, while s_{IEC}, s_{TPC}, s_{ASC}, s_{SLP}, and s_{REF} correspond to their normalized evaluations.

4.1 Weights Computation using the Simplified AHP

After defining the multi-level tree of criteria, the computation of weights was performed. We accomplished this task by applying a *simplified AHP*, based on pairwise comparisons and the *reduced scale* reported in Table 1. For each pairwise comparison, the respondents were asked to answer the following standard question: *"What is the relative importance of criteria A compared to criteria B?"*. The answers from 20 decision makers at the GSP were collected through an online survey.

Given the practical implication of our work, the rationale behind using a reduced scale, instead of the fundamental scale originally proposed by Saaty, is to simplify the collection of pairwise judgments, possibly minimizing inconsistencies.

Table 1: The reduced scale.

Relative Importance	Comparison Value
Strongly less	1/5
Moderately less	1/3
Equal	1
Moderately more	3
Strongly more	5

For each respondent and for each level of criteria, judgments were converted into comparison values and were recorded in comparison matrices such as the following one:

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & \dots \\ \dots & \dots & \dots & \dots \\ \dots & \dots & a_{ij} & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \quad (8)$$

where a_{ij} corresponds to the comparison value of criteria i compared to criteria j, $a_{ij} = \frac{1}{a_{ji}}$ and $a_{ij} = 1 \,\forall\, i, j : i = j$.

Given a comparison matrix, the relative weights of criteria were derived by applying the so-called "mean of row" method described by (Ishizaka and Labib, 2011), which is based on the following three steps:

1. Sum the elements of each column j: $S_j = \sum_{i=1}^{n} a_{ij} \,\forall\, j$
2. Divide each element a_{ij} by the relative column sum S_j: $a'_{ij} = \frac{a_{ij}}{S_j} \,\forall\, i, j$
3. Compute the mean of each row i: $p_i = \frac{\sum_{j=1}^{n} a'_{ij}}{n} \,\forall\, i$.

In group decision making contexts like ours, when several decision makers express their judgments, weights are combined by applying the geometric mean method (GMM) in order to obtain synthetic values for the entire group, as suggested by (Aczél and Saaty, 1983).

The aggregated weights obtained for the *macro* criteria are reported in Table 2. We define $\overline{p}_i$ as the aggregated weight for *macro* criteria i.

Table 2: Aggregated weights for *macro* criteria using the AHP.

i	IEC	TPC	ASC	SLP	REF
$\overline{p}_i$	0.1527	0.2672	0.1794	0.2394	0.1614

4.2 Weights Computation using the Revised Simos' Procedure

In order to verify the results obtained using the *simplified AHP*, we applied a second multi-criteria decision method (MCDM): the revised Simos' procedure proposed by (Figueira and Roy, 2002), which is particularly suitable to assess group decision processes with several sets of criteria. In this case, the experiment was restricted to a group of 8 decision makers at the GSP, whose answers were collected during individual interviews.

The experiment followed a four-step procedure which was repeated for each level of criteria, with the aim of collecting the necessary information to determine the weights of the criteria. The first three steps correspond to the original Simos' procedure, while the fourth step was introduced in the revised methodology proposed by (Figueira and Roy, 2002) in order to improve a few drawbacks of the original work. The whole procedure is described in the following:

1. Given a set of n criteria that have to be weighted, give the respondent a first set of n cards with the name of each criterion written on them. Then give the respondent a second set of white cards, having the same size. The number of white cards is not fixed, but it depends on the needs of the respondent.
2. Ask the respondent to rank the criteria in ascending order, from the least important to the most important. If some criteria have the same importance, they should be grouped together.
3. Ask the respondent to insert white cards between successive criteria (or subsets of *ex aequo* criteria) if a difference in terms of importance has to be highlighted. The principle of white cards insertion is simple: the greater the difference, the greater the number of white cards.
4. Finally, ask the respondent to estimate the relative importance of the last criterion (or subset of *ex aequo* criteria) compared to the first. This information is stored into the parameter z.

The computation of weights was performed by implementing the nontrivial algorithm proposed by (Figueira and Roy, 2002), where specific attention is paid to the rounding technique while determining the normalized weights of criteria.

Again, the aggregation of weights was obtained by means of the GMM. The so-derived aggregated weights for the *macro* criteria are reported in Table 3.

The results are consistent with those obtained using the *simplified AHP* and, except for REF *macro* criterion, they show an acceptable variation.

Table 3: Aggregated weights for *macro* criteria using the revised Simos' procedure.

i	IEC	TPC	ASC	SLP	REF
$\overline{p}_i$	0.1571	0.2608	0.1971	0.2676	0.1175

5 DSS IMPLEMENTATION

The DSS is composed by two main modules. The first one is a database that stores data regarding all suppliers available to the company and all the necessary information about contracts. The second module is then responsible for evaluating the score of each supplier according to the tree of criteria presented in Section 4.

As previously mentioned, when evaluating a given supplier, the score s_f is derived by means of an iterative *bottom-up* sum of the products of weights and normalized evaluations of *nano*, *micro* and *macro* criteria, in this order. The normalization process occurs in this second module and it is performed as follows:

1. For each criterion $i \in I$ and for each supplier $f \in F$ we are given an evaluation e_{if}.
2. For each set of evaluations e_{if} related to a particular criterion $i \in I$ we identify potential *outliers* by means of *box plots*.
3. In case of *direct* normalization (i.e., the greater the evaluation, the greater the normalized value we want to obtain), we compute the evaluation $E_{if} = e_{if}/e_{\max} \ \forall\ i, f$, where $e_{\max}$ is the maximum evaluation. The *outliers* take value 1, if they fall outside the external upper edge value of our *box plot*, and 0, if they fall outside the external lower edge value.
4. In case of *reverse* normalization (i.e., the greater the evaluation, the fewer the normalized value we want to obtain), we compute the evaluation $E_{if} = 1 - e_{if}/e_{\max} \ \forall\ i, f$, where $e_{\max}$ is the maximum evaluation. The *outliers* take value 0, if they fall outside the external upper edge value of our *box plot*, and 1, if they fall outside the external lower edge value.
5. The normalized evaluations E_{if} are then scaled in the interval $[0, 100]$.

Because the evaluation of suppliers depends on the information stored in the database (past and present), the score of a certain supplier may well change over time. For instance, as more contracts are assigned to the same supplier, it might become saturated, potentially reducing its score for future contracts.

In general, the proposed DSS is designed to retrieve updated information from the database of the company on a daily basis and recompute the score of each supplier. Then, every time a new contract is formalized, the decision makers can query the system, filter the returned ranking of suppliers, and use their experience to select the most appropriate from a reduced list of candidates. Note that, at this stage, it is important not only to consider the score of suppliers but also their distance from the facilities of customers. In this sense, to build the reduced list of candidates, we sort the suppliers according to the following weighted function:

$$\delta\, S_f + (1-\delta)\, D_{cf}, \tag{9}$$

where $f \in F$ and $c \in C$ are, respectively, the supplier being evaluated and the contract that we want to assign. $S_f = (s_f/s_{\max}) * 100$ expresses the score of supplier f, given the previously defined score s_f and the maximum score $s_{\max}$, whereas $D_{cf} = (1 - (d_{cf}/d_{\max})) * 100$ defines the *distance score*, given the geographical distance d_{cf} between the nearest branch of supplier f and the facility of customer associated with contract c, and the maximum distance $d_{\max}$. Both the score S_f and the *distance score* D_{cf} are normalized and scaled so that the result of (9) lies in the interval $[0,100]$. Finally, δ is a multiplier between $[0.1, 0.9]$ that controls the relative importance of each term of the aforementioned weighted function, and can be customized by the decision maker. To simplify, we refer to the aggregated value computed by this function as *assignment score*, given that it is associated with a specific assignment of a contract c to a supplier f.

In order to validate and assess the quality of the recommendations proposed by the system, we implemented a third module into the DSS. This module takes as input a list of contracts that were handled by the company on a certain day, and tries to select an appropriate supplier by means of a greedy heuristic algorithm. For each contract, the algorithm computes the *assignment score* for all available suppliers and assigns it to the one with the highest score. We report in the following page the pseudo-code of the proposed greedy heuristic algorithm, where $t \in T$ is a day in the simulation horizon T.

The results of the aforementioned simulation are stored in the database, so that when new contracts have to be assigned, the scores are recomputed and updated accordingly. The DSS architecture with all the three modules is depicted in Figure 2. Note that, with this structure, we are able to run simulations for any period of time based on past data from the company. However, it is worth mentioning that these simulations are intended to fine-tune the system and validate the recommended assignments together with the company. In practice, the DSS is designed to provide decision makers with the necessary tools to make an informed decision based on an ordered ranking of the best suppliers without automating the complete process, and it is meant to be integrated as a decision-making component within an ERP system, see, e.g., (Pekša and Grabis, 2018).

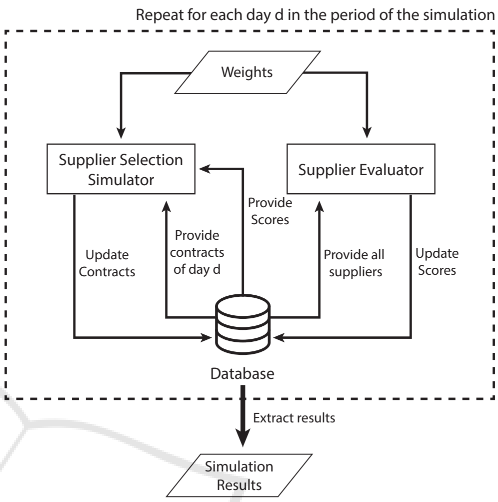

Figure 2: DSS architecture.

6 COMPUTATIONAL EVALUATION

The greedy heuristic algorithm presented in Section 5 was used to perform extensive simulations. We used different values for δ and a database of contracts associated with real-data from a seven-year period. The resulting assignments were evaluated by means of the aforementioned average score $\overline{S}_f$ and average *distance score* $\overline{D}_{cf}$.

Note that the generic distance d_{cf} between the facility of customer $c \in C$ and the branch of supplier $f \in F$ was evaluated using the following *haversine formula*:

$$d_{cf} = R\ \arccos(\cos\lambda_c \cos\varphi_c \cos\lambda_f \cos\varphi_f + \cos\lambda_c \sin\varphi_c \cos\lambda_f \sin\varphi_f + \sin\lambda_c \sin\lambda_f), \tag{10}$$

where R is the Earth radius, λ_c and φ_c respectively, the latitude and the longitude (in radians) relative to the facility of customer $c \in C$, and λ_f and φ_f, respectively, the latitude and the longitude (in radians) relative to the branch of supplier $f \in F$.

In our simulations, we experimented with $\delta \in [0.1, 0.9]$, thus resulting in a series of alternative solutions, which compose the *Pareto set* shown in Figure

Algorithm 1: Greedy heuristic algorithm pseudo-code.

Set a value of the multiplier δ
for $t = 1, 2, \ldots, T$ **do**
  Get the sub-list $\overline{C}$ of contracts to assign in day t
  if $\overline{C} \neq \emptyset$ **then**
    for $f = 1, 2, \ldots, F$ **do**
      Update ASC *macro* criterion
      Recompute supplier score s_f
    end for
    Normalize and scale the scores S_f in the interval $[0, 100]$
    for $c = 1, 2, \ldots, \overline{C}$ **do**
      for $f = 1, 2, \ldots, F$ **do**
        Evaluate the branch of supplier f having the shortest distance d_{cf}
      end for
      Normalize and scale the *distance scores* D_{cf} in the interval $[0, 100]$
      for $f = 1, 2, \ldots, F$ **do**
        Compute the *assignment score* $\delta\, S_f + (1 - \delta)\, D_{cf}$
      end for
      Assign contract c to supplier f having the highest *assignment score*
    end for
  end if
  Update the average simulation score $\overline{S}_f$
  Update the average simulation *distance score* $\overline{D}_{cf}$
  Update the average simulation distance $\overline{d}_{cf}$
end for

3. Each point in the chart represents a particular solution identified by an average score $\overline{S}_f$ and an average distance $\overline{d}_{cf}$ retrieved at the end of the simulation. For visual clarity, the average distance $\overline{d}_{cf}$ is expressed in kilometers, instead of using the normalized *distance score* $\overline{D}_{cf}$ computed in the weighted function (9).

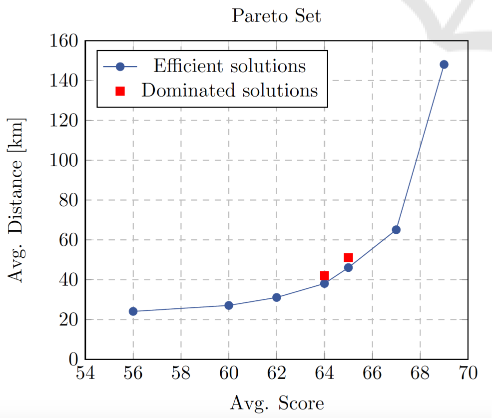

Figure 3: Pareto set resulting from different rounds of simulation.

Typically, the choice of the most desirable solution should be made by the decision maker at the GSP, according to what is considered the best trade-off between the average supplier score $\overline{S}_f$ and the average distance $\overline{d}_{cf}$. Note that, the two squared points identify likewise dominated solutions, so they are not even candidates to be the most desirable solution.

Table 4 reports the detailed results obtained by means of the extensive simulations performed for each multiplier δ. For example, looking at the column of the average *assignment score*, a decision maker might be willing to choose the solution identified by $\delta = 0.6$ as a good trade-off between the average supplier score $\overline{S}_f$ and the average distance $\overline{d}_{cf}$. Other good solutions are identified by $\delta = 0.3$, $\delta = 0.4$, and $\delta = 0.5$.

The results obtained from each round of simulation were duly shared with the company, compared to the incumbent assignments, and validated.

7 CONCLUSIONS

In this paper, we presented a supplier selection problem for a global service provider and proposed a decision support system to aid the decision makers at *H2H Facility Solutions S.p.A.* in the process of supplier evaluation and selection. In particular, the evaluation of suppliers was made by means of a thorough multi-criteria decision analysis performed in partnership with the company which led to the definition of a multi-level tree of criteria. The weights of criteria were computed by implementing a *simplified analytic hierarchy process* and a revised Simos' pro-

Table 4: Extended computational results.

δ	(1 − δ)	Avg. Score $\overline{S}_f$	Avg. Distance Score $\overline{D}_{cf}$	Avg. Assignment Score	Avg. Distance $\overline{d}_{cf}$ [km]
0.1	0.9	56	94	150	24
0.2	0.8	60	94	154	27
0.3	0.7	62	93	155	31
0.4	0.6	64	91	155	38
0.5	0.5	64	91	155	42
0.6	0.4	65	90	155	46
0.7	0.3	65	88	153	51
0.8	0.2	67	84	151	65
0.9	0.1	69	72	141	148

cedure. The results obtained with the two methods turned out to be reasonably similar. The DSS was implemented in a three-module architecture, where the first module is a database that stores information regarding contracts and suppliers. The second module is responsible for evaluating the score of each supplier, and the third simulates the assignment of contracts to suppliers based on a greedy heuristic algorithm and a weighted function, which evaluates an aggregated *assignment score*. The effectiveness of the proposed DSS was tested by means of extensive simulations over a seven-year period of real-data, identifying a series of alternative solutions. Given these alternative solutions, a decision maker can then choose the most appropriate one based on his/her experience.

In general, we found that the proposed approach is extremely flexible and highly repeatable. Therefore, it could possibly be adapted with some adjustments to other real-world supplier evaluation and selection problems, in different contexts as well. Indeed, in case of adaptation to other companies and industries, the proposed criteria should be slightly reconsidered in order to describe the problem of supplier selection in another context. However, once redefined the tree of criteria, the methodology might be fully replied.

As future work, we intend to perform a deeper computational evaluation of our methods, as well as to further investigate the selection of *macro*, *micro* and *nano* criteria, in order to express a few dimensions of the multiple criteria evaluation more exhaustively. In particular, it might be the case of refining the Economic indicators (ECI) in such a way that a more careful selection of *micro* criteria might lead to a more significant evaluation of economic soundness of suppliers. Then, with the aim of performing a detailed comparative evaluation, we intend to further develop the greedy heuristic algorithm, including additional dynamical aspects of the problem, such as an acceptable saturation level range for suppliers, a target number of active suppliers, and a proposal of organizational structure variations for suppliers in order to improve their score and, consequently, the probability to be selected. We also plan to develop more elaborated heuristic strategies. Finally, given the rising importance of GSPs in several sectors and the easy applicability of the proposed methodology, we are interested in implementing analogous DSSs, possibly embedding tailored heuristics, for other real-world applications.

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