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Dynamic MCDM with future knowledge for supplier selection

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Dynamic multi-criteria decision making (DMCDM) is an emerging subject in the decision-making area and in the last decade the challenge to consider time as an important variable has become important. Some frameworks already exist in this area but when compared with other types of decision-making models, DMCDM needs more work to be applicable in real industrial problems. In this work we extend a dynamic spatial-temporal framework, designed to deal with historical data (feedback), to address the problem of considering future information/knowledge (feed-forward). The main objective is to enrich dynamic decision-making models with explicit knowledge (existing historical data) and tacit knowledge (e.g. expert predictions) in time-evolving problems, such as supplier selection. Considering supplier-predicted information for future situations (e.g. investments in capacity) and, simultaneously, learning from historical data can help a company to find less risky and consistent alternatives. The proposed model is successfully implemented in a real case study for supplier selection in one automotive industry to demonstrate the capability and applicability of the model.

Keywords: dynamic MCDM; spatial-temporal decision making; supplier selection; future knowledge; historic information

1. Introduction

Most organisations consider neither available knowledge about suppliers' past behaviour nor tacit knowledge (e.g. from experts) about their future investments or trends, in their strategic decisions about supplier or business partner selection. There is a need for flexible decision models that contemplate including available knowledge (past and future) in the process of tactical and strategic decision-making, and supplier selection is a good example. Extending a dynamic multi-criteria decision-making model with future knowledge – the topic of this paper – is a good contribution to tackle that need.

Multi-criteria decision making models are commonly used in organisations to rationalise the process of decision-making (Figueira, Greco, & Ehrgott, 2005; Triantaphyllou, 2000). Usually the first assumption to simplify this type of problem is to assume that both criteria and alternatives are fixed a priori and that the decision occurs only once, i.e. no spatial or temporal considerations are included in the model. There is no doubt that with this assumption the validity of the result is rather limited, specifically when the values change over time and the decision matrix is not fixed or static. Moreover, since this work focuses on medium- or long-term decisions (tactical

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or strategic), spatial-temporal factors are crucial to ensure up-to-date and informed decisions. The challenge is really how to model knowledge in the decision process (Richards, 2002).

Recently, Campanella and Ribeiro (2011) proposed a general dynamic multi-criteria decision making (MCDM) model that combines feedback information (historical data) with current information, for each alternative, in a spatial-temporal decision process. Further, the dynamic decision model was adapted for a business-to-business general supplier selection process, with multiple inputs and multiple outputs (Campanella, Pereira, Ribeiro, & Varela, 2012), but without any consideration about future knowledge. However, this dynamic model only addressed past (historic) information, and in this work we advocate that future knowledge should also be considered, particularly for tactical or strategic decisions.

Hence, in this work, the above dynamic MCDM model (Campanella & Ribeiro, 2011) is extended to deal with future data. The future knowledge, which can also be called predicted information, can either be captured using prediction models or could be estimated based on expert knowledge or other available sources. Many decisions in companies are strategic decisions for the future, and these have been criticised for not considering future predictions, thus resulting in unrealistic decisions (de Boer, Labro, & Morlacchi, 2001; Ho, Xu, & Dey, 2010). Decision-making, using just current data, is a paradoxical challenge in management, whilst unstructured strategic decision-making requires a wider perspective, which deals with past and future data. In summary, this work addresses the problematic of considering time as a basic variable in the decision-making process, by including feedback and feedforward information in the classic MCDM problem. The feedback represents the past knowledge about suppliers' behaviour, and feed-forward represents the knowledge about future investments, trends, etc. Both can be merged to improve strategic decision-making processes in organisations. Finally, the main aim of this work is to enrich dynamic decision-making models with explicit knowledge (existing historical data) and tacit knowledge (e.g. experts' predictions) in time-evolving problems, such as supplier selection.

The paper is organised as follows. In the second section, related works about multi-criteria decision making for supplier selection are discussed. The third section introduces an extension for a dynamic MCDM model using both past and future information. In the fourth section the complete model is applied to a real supplier selection case study in the auto industry, to illustrate the versatility of the new approach, and, finally, in the last section the conclusion is presented.

2. Related work

The supplier evaluation and selection problem has been studied extensively and many decision-making approaches have been proposed to tackle the problem (good reviews can be found in Aissaouia, Haouaria, & Hassinib, 2007; de Boer et al., 2001; Ho et al., 2010).

In contemporary supply chain management, the performance of potential suppliers is evaluated against multiple criteria rather than considering a single factor-cost. Recently, Ho et al. (2010) reviewed the literature on multi-criteria decision-making approaches for supplier evaluation and selection. They analysed papers appearing in international journals from 2000 to 2008 with the aim of answering the following three questions: (1) which approaches were prevalently applied? (2) which evaluating criteria were paid more attention? (3) is there any inadequacy of the approaches? The research carried out by those authors (Ho et al., 2010) provide evidence that multi-criteria decision-making approaches are better than the traditional cost-based approaches, and also support researchers and decision-makers in applying the approaches effectively.

According to Ho et al. (2010) and Liaoa and Rittscherb (2007), supplier selection is a typical multi-criteria decision problem, which has been attracting great attention in the literature. Moreover, various decision-making approaches have been proposed to tackle the problem and, in contemporary supply chain management, the performance of potential suppliers is evaluated against multiple criteria rather than considering a single factor-cost.

In the opinion of Ng (2008), competitive advantages associated with the supply chain management philosophy can be achieved by strategic collaboration with suppliers and service providers. The success of a supply chain is highly dependent on selection of good suppliers. Simply looking for vendors offering the lowest prices is not an 'efficient sourcing' any more. Multiple criteria need to be taken into account when selecting suppliers.

As mentioned before, the supplier selection problem has received considerable attention in academic research and literature (Beil, 2010). In the 1960s, Dickson identified 23 criteria that ought to be considered by purchasing personnel in evaluating suppliers (Dickson, 1966). A later review by Weber, Current, and Benton (1991) reported that well over half of 74 research papers reviewed addressed the supplier selection problem with multiple criteria. Another comprehensive review by de Boer et al. (2001) discussed a framework for supplier selection. The framework covers different phases of the supplier selection process, including pre-qualification, formulation of criteria, final evaluation, etc. In the final evaluation phase of suppliers, after pre-qualification, quantitative models incorporating multi-criteria were constructed.

In general, supplier selection decision models are based on: multi-objective optimization (MOP) (Dahel, 2003; Weber, Current, & Desai, 1998, 2000); data envelopment analysis (DEA) (Liu, Ding, & Lall, 2000; Seydel, 2005; Weber, 1996; Weber et al., 1991, 1998); the analytic hierarchical process (AHP) (Bhutta & Huq, 2002; Chen, Lin, & Huang, 2006; Dahel, 2003; Lee, Ha, & Kim, 2001); and the simple multi-attribute rating technique (also called multi-criteria) (Ho et al., 2010; Seydel, 2005). These models provide systematic approaches for purchasing managers to evaluate and score suppliers with multi-criteria. Nevertheless, according to Ng (2008) many of those models are not easy to implement.

From the point of view of decision-making in organisations, the contemporary supply management target is to maintain long-term partnerships with suppliers, and use fewer but reliable suppliers. For example, Chan and Chan (2004; see also Degraeve & Roodhooft, 2000) state that because of the pressure of globalisation in the last two decades, outsourcing activities has become an important strategic decision so that supplier selection is a prime concern. The authors also state that, in fact, the selection problem is more crucial for the manufacturers of more complex scenarios, for instance sophisticated semiconductor assembly equipment, as these are multi-item, multi-person and multi-criterion decision problems.

Therefore, choosing the right suppliers involves much more than scanning a series of price lists, and choices will depend on a wide range of factors. In this work, we advocate that this problem belongs in a spatial-temporal context, where the solution requires the capability to handle changeable input criteria and alternatives, evolving in a time frame. Further, we believe that dynamic MCDM is an effective approach to solve the problem of supplier selection, when time is considered, in terms of both past behaviour and future information.

3. Extended dynamic model with future knowledge

3.1. Problem context

To manage complexity in real decision-making problems, there are different types of strategies, which can simplify the problem by using some assumptions. The common strategy is to consider the situation time-independent and model the problem in a static situation. In this case, many important factors will be disregarded and in some cases it will result in erroneous decisions. Furthermore, most tactical and strategic decisions in companies require some thought and time, sometimes even undergoing internal negotiations between departments, to reach a final decision, i.e. these types of decisions are spatial-temporal dependent.

MCDM is a technique widely used (Barba-Romero 2004; Figueira et al., 2005) for selection problems, but traditionally there is no relation between basic and supportive variables using MCDM models. By assuming a fixed time frame to develop the decision matrix it means knowledge from past and future information is not employed to support more informed decisions. Further, discretising the time frame and using aggregation methods may also be quite helpful (Barba-Romero, 2004).

The following matrix depicts the classical MCDM model where a_i, i=1…m represents the ith alternative for decision-making, C_j, j=1…n is the weight of the jth criterion and x_{ij} is the decision parameter representing the level of achievement of alternative a_i with respect to criterion C_j. x_{ij} could be any normalised number from 0 to 1 where 0 means 'no satisfaction' and 1 corresponds to complete satisfaction.

$$\begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \qquad (1)$$

In the above decision matrix (1), the assumption is that x_{ij} is considered to be time independent when, in real applications, usually the decision matrix evolves with time. As pointed out by Richardson and Pugh (1981), dynamic decision problems have two main features: (a) they are dynamic because they involve quantities which change over time; (b) they involve the notion of feedback.

In reality, most tactical and strategic decisions (the focus of this work) have spatial-temporal limitations because the search space varies for each step (iteration) and there are several steps (iterations) to reach a final decision. During any dynamic decision process, many aspects may change, such as: (1) the available set of alternatives can increase or decrease (e.g. one supplier went out of business), (2) new criteria must be added (e.g. time to deliver was not considered), (3) or other criteria no longer apply in the specific context (e.g. production capacity).

Another identified problem of static decision-making – tactical or strategic decisions – is the lack of consideration of future information, due to previous actions (e.g. investments in new machinery to improve capacity) or forecasts of alternatives for the next period.

From the above statements the two major drawbacks identified in the classic MCDM model are the following:

- Historical data. This type of data refers to past judgements made, regarding the available alternatives. It can have a crucial impact in the current decision process, because alternatives with a 'bad' historic behaviour will affect the current decision and vice-versa. For example, if a certain supplier always delivered the products late, this knowledge should affect our decision to continue or stop cooperating with it. We need to find a solution for considering past experiences in the decision-making process.

- Future knowledge. The decision is based on the current situation; however, employing future information could bring added value to support the decision. As an example, a supplier with a high probability of bankruptcy should not be selected, even if he could meet all current targets (criteria). This is an exaggerated case but demonstrates the crucial role of future knowledge.

To overcome the two drawbacks, this work presents an extension of the dynamic model (Campanella & Ribeiro, 2011) – which already addresses past information – by including future knowledge. The aim is to enable dealing with tactical and strategic decisions, which are usually taken over time.

3.2. *Proposed dynamic model with future knowledge*

The first step in the classical MCDM (Figueira et al., 2005) is to identify the available alternatives, selecting relevant criteria to evaluate each alternative, and develop the decision matrix based on the level of satisfaction of each alternative for each criterion. This phase is called preference elicitation. The next step is the aggregation of all values for each alternative to achieve a final value for each alternative (rating) so they can be ranked.

Further, in the classic MCDM, there is only one matrix reflecting the current status of the system, while in the dynamic MCDM (DMCDM) model (Campanella & Ribeiro, 2011; Campanella et al., 2012) at least two matrices must be considered: the historic matrix, which represents the situation in the past, and the current matrix, which represents the current status. At each period (time or iteration) the two matrices are combined and the result stored (updated historic data) for the next iteration. Further, DMCDM allows dealing with changing inputs, by updating current information and/or removing or adding new alternatives or criteria. Details about the mathematical formulations for this dynamic decision-making model can be seen in (Campanella & Ribeiro, 2011).

Here, we extend this dynamic model with a 'future knowledge matrix' representing the estimated future values for certain criteria to evaluate the alternatives of the current situation. The past status is based on historical data and the future state is based on future knowledge, which could be derived from predicted information. The future or predicted knowledge can be calculated either by using a quantitative model or experts' knowledge. The future or predicted information could also be generated by negotiation and estimation.

For any specific context, different logics could be employed to develop the future decision matrix. For example, in the supplier selection case, it is important to know their future investments, such as investment in infrastructure and technology and/or their predicted/forecast data for the next period. Nowadays, most managerial performance frameworks consider some criteria, classified as 'enabler', to take the future of the company into account, and this shows the importance of considering future data (Bou-Llusar, Escrig-Tena, Roca-Puig, & Beltrán-Martín, 2009; Campanella & Ribeiro, 2011; Campanella et al., 2012; de Boer et al., 2001).

Finally, to calculate the final utility for each alternative, the three types of matrices – historical, current and future information – are combined to achieve an aggregated value for each alternative (usually called rating or score). This aggregated value is the rating for each alternative, at any given period, where the decision about supplier selection takes place (e.g., every 6 months).

Summarizing, with this approach we take into consideration past, current and future information, with the aim to achieve improved and better-informed tactical or strategic decisions. It is important to have consistency in suppliers' behaviour, so past evaluations (historical matrix) shall affect our decisions. The current matrix reflects the latest situation and the future matrix reflects the expectations for the next period or iteration. Figure 1 depicts the extended DMCDM concept of merging the three types of matrices to rate and rank suppliers at each evaluation period (dynamic process).

To improve readability the figure assumes a fixed set of alternatives and criteria,but these can change, as discussed previously. Furthermore, in the three matrices of Figure 1, xij represents the satisfaction of criteria C for alternative A.

An important challenge of this model is how to aggregate the three decision matrices to have one final score to represent the rating of each supplier. The first step is how to aggregate the respective criteria values of each individual matrix, resulting in three vectors, one for each matrix (see Figure 1). The second step is to merge (aggregate) the three resulting vectors into a single score for each alternative, which includes past, current and future information. There are many operators to perform the two aggregation steps and their usage in multi-criteria problems is widespread (Beliakov, Pradera, & Calvo, 2008; Calvo, Mayor, & Meisar, 2002; Ribeiro, Pais, & Simoes, 2010). Several

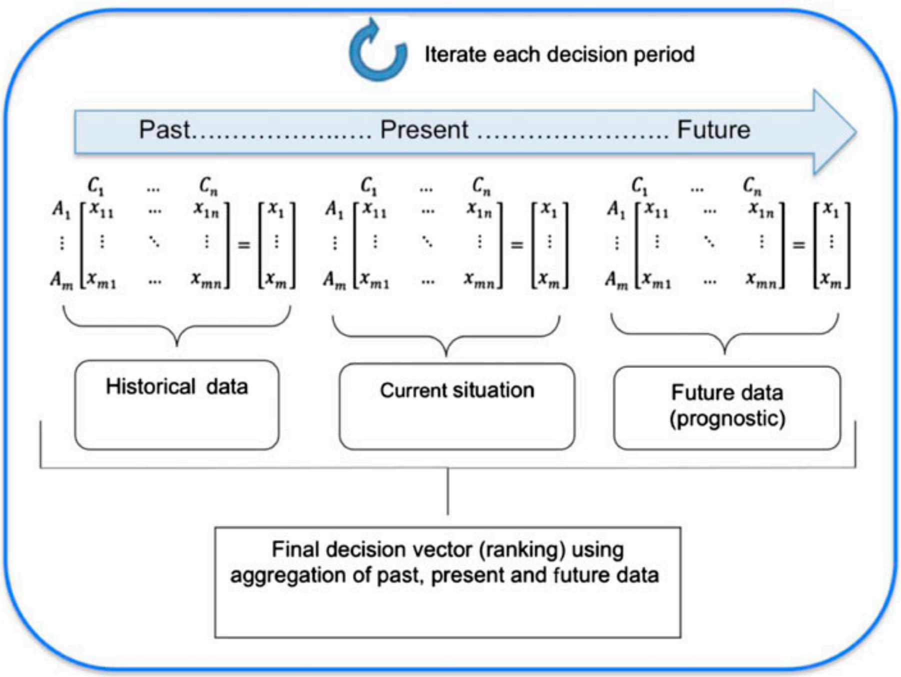

Figure 1. Extended dynamic multi criteria decision making (DMCDM) model with prognostic.

classes of aggregation operators are proposed in the literature, from weighted average methods to conjunctive methods, scoring methods, maxmin, parametric, reinforcement and so forth – and choosing the appropriate one is an important subject (Beliakov et al., 2008). Some common examples are introduced in the following table:

In our case study, we will use the simple weighted average to clarify understanding of the extended dynamic model, but any other operator could have been used, and in the future we intend to perform a comparative study using other operators for supplier selection problems. After determining the final decision vector (Figure 1) the ranking can be obtained by ordering the alternatives and selecting the supplier with the highest score.

4. Case study

This case study is based on data from a real car manufacturer company. The case study data refers to a Middle East automotive manufacturing company, here called EAM. For reasons of privacy we do not show the names of the suppliers. We also made some

Table 1. Common aggregation operators from non-parametric to synergetic (adapted from Li et al., 2004).

Symbol	Description
a1,a2	Two input values, which represent possible satisfaction values of an alternative, for two criteria
min	The minimum value of (a1,a2)
max	The maximum value of (a1,a2)
Weighted sum	((w1*a1)+(w2*a2))/n, where n= number criteria and sum of weights =1
Hammacher intersection	Synergetic operator, either increasing (union) or decreasing (intersection). For example, the synergetic intersection (parameter β controls the synergy) is: $H(a1, a2) = \frac{a1+a2}{\beta+(1-\beta)*(a1+a2-a1*a2)}$
FIMICA	Full-reinforcement operator. For example an additive FIMICA linear function for three criteria can be defined as: $f1(a1, a2, a3) = \begin{cases} 0 & \Sigma \leq 0 \\ \Sigma & 0 < \Sigma < 1 \\ 1 & \Sigma \geq 1 \end{cases}$ Where, $\Sigma = ((a1 - g) + (a2 - g) + (a3 - g) + g)$ and g is the neutral element controlling the reinforcement positive or negative reinforcement level.

Table 2. Input data for the year 2009.

EAM (2009)	Price of unit	On time delivery performance	Defect free delivery	Production capacity (monthly)	Product variety
Supplier 1	364300	85%	96%	15000	3
Supplier 2	346085	80%	93%	8000	3
Supplier 3	375600	90%	98%	17000	3
Supplier 4	356820	85%	95%	8000	3
Supplier 5	349680	96%	96%	6000	2
Supplier 6	339160	85%	95%	6000	2
MAX		0.96	0.98	17000	3
MIN	339160				

Table 3. Dynamic decision results for 2009 (first iteration).

	Normalized values for the year 2009					Scores 2009	Decision w/ Forecasting
EAM (2009)	Price	On time delivery performance	Defect free delivery	Capacity	Product variety	Current (c1)	Decision t1 = (c1, c2)
Supplier 1	0.931	0.885	0.980	0.882	1.000	0.933	0.9527
Supplier 2	0.980	0.833	0.949	0.471	1.000	0.902	0.8895
Supplier 3	0.903	0.938	1.000	1.000	1.000	0.952	0.9550
Supplier 4	0.951	0.885	0.969	0.471	1.000	0.915	0.9312
Supplier 5	0.970	1.000	0.980	0.353	0.667	0.936	0.9316
Supplier 6	1.000	0.885	0.969	0.353	0.667	0.874	0.8836
4-best RANKED						S3>S5>S1>S4	S3>S1>S5>S4

small changes to the data to provide a better demonstrative case (e.g. we considered semester data as yearly data).

Usually, car manufacturers and suppliers prefer long-term contracts, which should be reviewed at least every year. To make better-informed tactical/strategic decisions, it is very important to know the historical data as well as having some knowledge about the future situation of the supplier. In this case study, we only had access to data from EAM for four years (2009, 2010, 2011 and 2012) for its six suppliers. Therefore, in the first iteration, we obtained the ratings for 2009 using only current and future data (2009 and 2010). For the 2010 decision rating, we used the 2009 rating as past information, 2010 as current information, and 2011 as future information. For 2011 we used the same process but without future information.

The EAM company is categorised as a manufacturer of high-tech parts for the automotive industry and evaluates its suppliers' performance with the following measures: 'price of unit', 'on-time delivery performance', defect-free delivery', 'product variety' and 'product capacity'. Therefore, the criteria used in this work to rank the suppliers with our extended dynamic model are the real criteria of EAM.

Usually, most auto-parts manufacturing companies consider few suppliers as potential partners. This can help them to have a better understanding, build mutual trust and increase loyalty in the supply chain. Further, depending on their rating, the listed suppliers have a better chance to win the contract for a fixed period of time. The limited number of suppliers is due to the limited number of available suppliers that can be trusted by the headquarters company, and also the specificity of the business. Furthermore, automotive companies prefer to work with a limited number of suppliers to build long-term partnerships and enable pushing suppliers to increase their ability and performance. For EAM there are six registered suppliers.

In this work, we will use simplified semantic weights to clarify our approach: (1) price of unit, on-time delivery performance and defect-free delivery criteria are all very important (without differentiation); (2) product variety and production capacity are considered not important. Hence, for a first simulation, the normalised weights used were (sum = 1): 30% for the very important criteria and 5% for the not important. After, to assess the robustness of the approach, we considered different weights: 40% for deliverable time and 25% for the other two important criteria. The results obtained in terms of ranking were exactly similar, which clearly demonstrates that the results are not too sensitive to changes in the importance/weights of criteria.

Since we did not have predicted data (future knowledge) for the suppliers, we used the data from the years ahead, i.e. for 2009 we used the data of 2010, and so forth.

Table 4. Input data for the year 2010.

EAM (2010)	Price of unit	On time delivery performance	Defect free delivery	Production capacity (monthly)	Product variety
Supplier 1	395400	95%	98%	19000	4
Supplier 2	375630	85%	96%	9000	4
Supplier 3	403500	90%	98%	22000	4
Supplier 4	383325	90%	98%	11000	4
Supplier 5	375650	90%	97%	12000	2
Supplier 6	368110	89%	96%	8000	2
MAX		0.95	0.98	22000	4
MIN	368110				

Table 5. Dynamic decision results for 2010 (second iteration).

	Normalized decision matrix for the year 2010					Score 2010	Score w/ historic data	Decision w/ past & forecast
EAM (2010)	Price	On time delivery performance	Defect free delivery	Capacity	Product variety	Current (c2)	h1 = (c2,t1)	Decision t2 = (h1, c3)
Supplier 1	0.931	1.000	1.000	0.864	1.000	0.9725	0.9527	0.9591
Supplier 2	0.980	0.895	0.980	0.409	1.000	0.8767	0.8895	0.9152
Supplier 3	0.912	0.947	1.000	1.000	1.000	0.9579	0.9550	0.9593
Supplier 4	0.960	0.947	1.000	0.500	1.000	0.9473	0.9312	0.9410
Supplier 5	0.980	0.947	0.990	0.545	0.500	0.9274	0.9316	0.9287
Supplier 6	1.000	0.937	0.980	0.364	0.500	0.8931	0.8836	0.9018
4-best RANKED						S1>S3>S4>S5	S3>S1>S5>S4	S3>S1>S4>S5

Although this is not predicted or future knowledge, it mimics a similar behaviour, and for clarification of the decision process it is enough. It should also be stressed that even if some future or past criteria do not exist, the dynamic model will still operate, because the number of criteria and alternatives can change with time. The dynamic MCDM model is spatial-temporal and, therefore, robust to accepting changeable input data, alternatives and criteria (Campanella & Ribeiro, 2011).

In Table 2, we depict the raw input data for year 2009, as well as the maximum and minimum of each column, to allow us to normalise the criteria values. To normalise the values of the decision table, the maximum and the minimum value are used depending on the logic behind each criterion. For the price of unit criterion, 'lower is better', so the values are divided by the minimum, while for the other criteria the logic is 'higher is better', so to normalise the values they are divided by the respective maximum per criterion/column. After generating the normalised decision matrix, the final score for each supplier is determined with a simple weighted average, with the weights described above (30% for the first three criteria and 5% for the other two).

4.1. *First iteration of dynamic decision*

In the first iteration, we only have access to current and future information. Table 3 depicts the normalised values (from Table 2) and the resulting criteria aggregation for 2009 (time t1) with future information (f1) from 2010. The last column is the result of aggregating these two scores, 2009 and the considered values for 2010.

In this first iteration, there is no historical data so the process for selecting suppliers in 2009 is finished. Observing the rankings (last line in Table 3), the first classified is the same (S3) for both the current evaluation and the one with forecasting information; however, the second classified changed, and supplier 1 (S1) is chosen instead of supplier 5 (S5), because S1's expected behaviour for 2010 will improve.

4.2. *Second iteration of dynamic decision*

In the second iteration, which refers to the year 2010, we are now able to consider both historic data (2009) and future data (2011). This implies that we can take full advantage of the extended dynamic model and use past, current and future information for making more informed decisions. Tables 4 and 6 show the raw input data for 2010 and 2011 (future data).

Table 6. Input data for the year 2011.

EAM (2011)	Price of unit	On time delivery performance	Defect free delivery	Production capacity (monthly)	Product variety
Supplier 1	424630	100%	100%	24000	4
Supplier 2	403398.5	92%	98%	14000	5
Supplier 3	433400	100%	100%	26000	4
Supplier 4	411730	95%	99%	16000	5
Supplier 5	403490	94%	97%	15000	3
Supplier 6	395330	92%	97%	12000	3
MAX		1	1	26000	5
MIN	395330				

Table 7. Dynamic decision results for the year 2011 (third iteration).

	Normalized values for the year 2011					Score 2011	Score w/ historic data	Decision w/ past & future (2011)
	Price	On time delivery performance	Defect free delivery	Capacity	Product variety	Current (c3)	H2 = (t2,c3)	Decision t3 = (h2,c4)
Supplier 1	0.931	1.000	1.000	0.923	0.800	0.9655	0.9690	0.8361
Supplier 2	0.980	0.920	0.980	0.538	1.000	0.9409	0.9088	0.8042
Supplier 3	0.912	1.000	1.000	1.000	0.800	0.9636	0.9608	0.9588
Supplier 4	0.960	0.950	0.990	0.615	1.000	0.9508	0.9491	0.9516
Supplier 5	0.980	0.940	0.970	0.577	0.600	0.9258	0.9266	0.9329
Supplier 6	1.000	0.920	0.970	0.46	0.600	0.9201	0.9066	0.7906
4-best RANKED						S1>S3>S4>S2	S1>S3>S4>S5	S3>S4>S5>S1

Table 5 shows the normalised values and also the three results of using the extended dynamic decision model: (1) the current iteration scores (2010), (2) the result of aggregating current scores with historic (past) information (2009 and 2010) and (3) thefinal decision results obtained by aggregating past and current with forecast information (2009, 2010, 2011). As can be observed in the results, the rankings of this iteration diverge when we consider historic and future information. Supplier 3 (S3) would be selected without using the proposed dynamic process (i.e., just the current score), but when we consider historic and future data the best ranked is S1. The results difference between using just historic or using historic and future information is clearly visible in the last-ranked supplier, S4, because this one is making an effort to climb the ladder and become a competitor with the aim of obtaining future contracts to supply EAM.

Summarizing, the results of Table 5 show the crucial role time can play in the decision-making process, as well as the impact of considering both historical data and future information. The message is clear: to have a better rank, suppliers must have a defendable past history of behaviour and also demonstrate their willingness (e.g., future investments) to improve their performance. The winners will be balanced suppliers throughout time and robust long-term partnerships between companies and their suppliers.

4.3. *Third iteration of the extended dynamic model*

Table 6 shows the input raw data for 2011, and Table 7 depicts the results obtained for 2011, using as future information the raw data of 2012 (Table 8).

In Table 7, it is clear that Supplier 3 improved its future situation (in this iteration future data refers to 2012 data) and, therefore, it is ranked first when both historical and future information are taken into account. Supplier 1 is the first ranked when we only consider the current and past information; however, if we take into account future information it clearly falls behind S3, S4 and S5. Another aspect observed in Table 7 is that Supplier 2 is only considered in the top four suppliers list if neither historic behaviour nor historical and future data are included in the decision-making process. This result clearly shows that considering only current information is quite limiting and can lead to erroneous decisions, because we know that Supplier 2 did not behave well in the past and is not going to improve in the near future!

Table 8. Input data for the year 2012.

EAM (2012)	Price of Unit	On time delivery performance	Defect free delivery	Production capacity (monthly)	Product variety
Supplier 1	456100	95%	100%	30000	5
Supplier 2	433295	98%	99%	18000	6
Supplier 3	48299	100%	100%	31000	5
Supplier 4	44250	98%	100%	18000	5
Supplier 5	42700	95%	99%	20000	3
Supplier 6	424620	95%	99%	18000	4
MAX		1	1	31000	6
MIN	42700				

Table 9. Dynamic decision results for 2012 (fourth iteration).

	Normalized values for the year 2010					Score 2012	Decision w/ historic data
EAM (2012)	Price	On time delivery performance	Defect free delivery	Capacity	Product variety	C4	Decision t4 = (c4, t 3)
Supplier 1	0.094	0.950	1.000	0.968	0.833	0.7031	0.828
Supplier 2	0.099	0.980	0.990	0.581	1.000	0.6996	0.795
Supplier 3	0.884	1.000	1.000	1.000	0.833	0.9569	0.956
Supplier 4	0.965	0.980	1.000	0.581	0.833	0.9542	0.943
Supplier 5	1.000	0.950	0.990	0.645	0.500	0.9393	0.935
Supplier 6	0.101	0.950	0.990	0.581	0.667	0.6745	0.779
4-best RANKED						S3>S4>S5>S1	S3>S4>S5>S1

Table 10. Summary of top four suppliers' rankings through time.

Year	Ranking for current data	Ranking with historical data	Ranking with historical data and future information
2009	S3>S5>S1>S4	NA	S3>S1>S5>S4 (No historical data)
2010	S1>S3>S4>S5	S3>S1>S5>S4	S3>S1>S4>S5
2011	S1>S3>S4>S2	S1>S3>S4>S5	S3>S4>S5>S1
2012	S3>S4>S5>S1	S3>S4>S5>S1	NA

4.4. *Fourth iteration of the dynamic model*

In this iteration, since we do not have real predicted or estimated data for 2013, the dynamic final decision only includes the current score and its corresponding historic behaviour. Table 8 shows the raw input data and Table 9 shows the results for this last iteration (year 2012).

As can be observed in Table 9, in the year 2012, the ranking is identical when using only current or current and historical data. One possible explanation is that the suppliers' satisfaction of criteria is becoming more homogeneous due to feedback from the clients, e.g. from previous iterations.

Table 10 summarises the ranking positions of suppliers in the four years studied, to enable a better comparison of the effect of considering historical data as well as future knowledge in the extended dynamic decision model.

Observing Table 10, it is interesting to note that supplier 3 (S3) is consistently better when we take in consideration historic and future information. Supplier 1 is a good competitor (results for 2010 and 2011) when we do not consider future information, but in the last year its behaviour has fallen badly (last in the top four).

As a final comment, this case study demonstrated how important it is to consider temporal data (both past and future information) when a company is evaluating suppliers to ensure the maintenance of long-term partnerships with suppliers, and to use fewer but reliable suppliers. It should be noted that, even without proper predicted or estimated information (here we used the data for the next year as future information), the importance of using spatial-temporal (dynamic) decision models is clearly demonstrated.

As mentioned in the discussion of related work, Section 2, with the pressure of globalisation and increase in outsourcing activities, supplier selection is nowadays a prime concern and a crucial strategic decision in any company. Further, strategic decisions are, most of the time, taken in spatial-temporal contexts and the proposed extended dynamic MCDM, considering past and future information, will be essential to ensure appropriate and reliable long-term relationships with suppliers.

5. Conclusion

This work extended the dynamic decision making model proposed by Campanella and Ribeiro (2011) to consider not only historic information (past knowledge) about suppliers' behaviour but also predicted information (future knowledge) about them. The advantage of this extension is to include the impact of past and future information in any dynamic decision process, thus enabling more informed decisions with enriched information. The applicability of the introduced model was demonstrated with a real-world problem, therefore showing how crucial it is to have a holistic view and a wider perspective about supplier selection.

Further, the introduced dynamic model enables decision-making in dynamic contexts, where spatial-temporal considerations are addressed, such as the case of almost all strategic decisions and many tactical ones.

As future work, we plan to use different aggregation operators (Beliakov et al., 2008; Ribeiro et al., 2010), such as synergetic and/ or reinforcement ones, to enable assessing the robustness and versatility of the dynamic method. Further, we plan to find another comparative example where predictive or prognostic information exists, to allow us to perform a more in-depth analysis of the impact of using an extended dynamic approach for supplier selection.

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