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Reducing data requirements when selecting
Key Performance Indicators for Supply Chain Management:
The case of a multinational automotive component manufacturer

Abstract

The recent trend towards collecting large amounts of data potentially allows organisations to identify previously unknown data patterns that can lead to significant improvements in their performance across the whole supply chain. However, carrying on collecting this data over time and across numerous locations is expensive. Consequently, when monitoring performance, organisations can be faced with a dichotomy between continuing to collect large amounts of data or whether to use a much reduced set of data. This is a particular problem with Key Performance Indicators (KPIs). Additionally, too many indicators can lead to difficulty in data interpretation and significant overlaps between the indicators, making the understanding and managing of changes in performance more difficult. In this paper, a novel statistical approach is introduced based on the use of Principal Component Analysis (PCA) to reduce the number of KPIs, followed by using TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) for validating the results. It is applied to the case of a multinational automotive component manufacturer where 28 KPIs were reduced to 8. The performance of the original set of 28 KPIs was compared with that of the reduced set of 8 KPIs. The peaks of the two TOPSIS time-series coincided, and there was a high correlation between them. Therefore, having the extra 20 indicators provided little extra precision for the considered time interval. Hence, the approach is a valuable tool in helping to reduce a large number of KPIs down to a more practical and usable number.

Keywords

Key Performance Indicators; TOPSIS; Principal Component Analysis; Supply Chain Management

1. Introduction

A major direction in Operations and Supply Chain Management over the last few years has been the collection and analysis of increasing amounts of data. The hope has been that collecting evermore data and then employing data analytics, would provide organisations with insights that would be commercially advantageous. However, when monitoring an organisation's performance, the potential benefits from gathering large amounts of data, need to be offset against the difficulty for managers to interpret the high dimensional results. This conflict is well established in the literature (see below), and is a particular problem for Key Performance Indicators (KPIs) as assessing an organisation's success is a multi-dimensional and subjective matter. Consequently, we propose and analyse an approach that allows organisations to manage the conflicting objectives of fully utilising the big data that they can now capture, and the need to be able to incorporate management understanding into any subsequent analysis.

Most large organisations use KPIs as a decision-aiding tool in order to manage their business and their supply chains, with management strategy connecting the KPIs to the organisational goals (Okoshi et al., 2019). However, selecting good indicators can be difficult as their effects on ultimate business goals (such as profits) are often indirect and not easily quantifiable (Franceschini et al., 2007). Choosing too few indicators can lead to important factors being overlooked. On the other hand, choosing too many indicators has the disadvantage of diverting attention away from the factors that actually make a difference to the company's performance while incurring additional costs due to the extra data collection (Almeida and Calistru, 2013). Consequently, (Brown, 1996) noted that when constructing performance measurement systems:

> "*The most common mistake organizations make is measuring too many variables. The next most common mistake is measuring too few.*"

This is echoed by Chae (2009) who notes that contrary to the common belief that an increase in the volume of information is better, when it comes to KPIs "*the less is better*", keeping the information used for control and monitoring to that which is necessary. Hawkins (2004) notes that having too many predictors affects, amongst other things, the portability of the model. Although the problem of having too many performance indicators in supply chain management has been recognised as a significant issue for over 20 years (e.g. Brown, 1996), very little has been reported on practical applications of statistical and multi-criteria decision-making approaches for reducing a large set of indicators to a more manageable subset.

This problem will continue to grow as there are several reasons for the continued increase in the amount of performance data that is collected. For instance, the increasing relevance of the sustainability discourse in Supply Chain Management, along with the emergence of the Circular Economy paradigm (Genovese et al., 2017a), requires organisations to monitor their performance across an even wider range of measures (mainly environmental and social ones) (Genovese et al., 2017b). For this reason, several large industrial organisations are launching Big Data programmes. Due to the quantity of data within such projects, knowing what is most valuable to the firm can drive the success of the massive data acquisition and processing efforts. According to Fanning (2016), the effectiveness of such programmes can be enhanced by the careful selection of a set of

KPIs, which can provide a useful way to prioritise organisational values and goals in a Big Data environment.

The approach proposed in this paper is based on the subsequent use of (i) an objective statistical approach using Principal Component Analysis (PCA) for selecting the most efficient and effective subset of KPIs and of (ii) the TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) method for validating the selection process, by comparing the performances of the initial and the reduced set of KPIs. In particular, PCA is employed to find the main latent variables present in the full set of KPIs. Performance indicators that are strongly correlated to these principal latent variables are then identified and form the reduced set of KPIs (*selection step*). As the full and reduced sets of KPI are not normally aggregated into a single score as they are time series, it is not possible to directly compare the performances of the two sets of indicators to validate the selection process. For this reason, alternative approaches are needed. Our proposal consists in employing TOPSIS to assess how well the reduced set of indicators mirrors the performance predicted by the full set. While TOPSIS has been used in conjunction with KPIs (see, e.g. Tavassoli, 2020), to the best of our knowledge, it has never been used to compare the information contained in the full set of KPIs with the information in a reduced set of KPIs created by using PCA. Its employment in this sort of validation step represents a key, novel feature of the approach and it is particularly useful when indicators are not aggregated in to a single score and cannot be directly compared.

The proposed methodology is applied to the case of a large multinational company from the automotive sector, specialising in the manufacture of high complexity aluminium components. The highly resource intensive nature of the automotive manufacturing industry (Amrina and Yusof, 2011) means that good access to prompt and accurate KPIs is an important factor for successful business operations (Chae, 2009). One of the regional areas of the company developed an extensive set of supply chain related indicators in the form of a scorecard. This supply chain scorecard was conceived as a regional solution, but its perceived success led to a desire to adopt the scorecard for its use in global performance comparison, evaluation and decision making. However, the large, unwieldy number of indicators included in the scorecard was an obstacle to this international roll out. Consequently, the objective behind the methodology was to reduce the number of indicators to the best possible set .

The remainder of this paper is organised as follows: the next section provides a literature review on the usage of KPIs for benchmarking supply chains, followed by the description of the methodological details of the approach proposed for selecting the KPIs. The case study is then described, before the presentation and the discussion of the results obtained from the application of the methodology. Finally, some conclusions are drawn.

2. KPIs for Supply Chains

Although the principles underlying the construction and usage of KPIs are universal, the choice of indicators is specific to different management areas, and within these areas, it is specific to different industrial sectors (Christopher and Towill, 2002). The measurement of supply chain performance has been receiving increasing attention in the past decades because it plays a vital role in business related activities, manufacturing and services industries, in increasing their efficiency, effectiveness and overall profitability (Cai et al., 2009; Katiyar et al., 2015; Taticchi et al., 2015). Performance metrics or KPIs offer an overall visibility of the supply chain, helping to asses its performance and revealing potential opportunities (Chae, 2009). Gunasekaran et al. (2001) provide a list of potential performance measures that can be used to assess Supply Chains, while Gunasekaran et al. (2004) present an overview on the different levels of measurements involved in Supply Chain Management. *Strategic level measurements* mainly influence the top management decision-making, offering a wider overlook of the company policies and corporate plans; *tactical measurements* manage resource allocation to achieve company targets, whereas the *operational level* metrics include the assessment of accurate data for decision-making by lower management that lead to the accomplishment of the tactical objectives. Moreover, Angerhofer and Angelides (2006) highlight the importance of collaboration among the different levels of metrics, in such a way to increase the benefits and alignments of the different managerial decisions involved in the supply chain to achieve the business objectives. The drivers for success in a Supply Chain Management performance measuring system are the commitment of the top management, consistency whithin the objectives and an effective information system (Charan et al., 2008). A key challenge is the effective identification and selection of KPIs to accomplish the latter two tasks (Cai et al., 2009).

Turning to the automotive sector, major companies co-operate with hundreds of different suppliers around the globe ranging from consumables to key components, meaning that the automotive supply chain is highly complex when compared with most other production networks (Scannell et al., 2000, Olugu et al., 2011). Therefore, there is a need for well chosen performance metrics facilitating more open and transparent interactions among the supply chain members (Schmitz and Platts, 2004; Gunasekaran and Kobu, 2007). In particular, increased understanding between the partners enables more flexibility in the supply chain which can be particularly advantageous in the technologically complex automotive supply chains (Martinez Sanchez and

Perrez Perez, 2005). Hence, the KPIs need to be simple to aid this understanding (Krakovics et al., 2008).

Katiyar et al. (2015) summarise in twenty different factors the main KPIs from the literature and adapt them to the automotive industry. These range from "hard" factors such as quality or product cost to "soft" ones like buyer-supplier relationship or flexibility. Nevertheless, there is no unique set of KPIs that successfully presents in a single picture the performance of the different axes of the supply chain.

Estampe et al. (2013) summarise different available performance evaluation models, such as the Balanced Scorecard and Supply Chain Operation Reference (SCOR), identifying their similarities and scopes, and providing a table for guidance on which ones are appropriate for which situations. However, a common problem for all of them is how to choose, prioritise and weight performance indicators. Various issues can arise; for example, having an extensive variety of individual measurements for a supply chain context may be desirable but it is likely to be difficult to obtain values for the different member of the supply chain participants. Another problem is the difficulty in identifying cause-effect patterns due to the interactions and overlaps among the indicators (Cai et al., 2009). Saad and Patel (2006) found that the performance indicators were focused on technical and tangible factors whereas measuring and improving relationships was not regarded as a high priority. Gunasekaran and Kobu (2007) concluded that an effective performance management system should be reliable, practical and compatible with the existing information systems with easy measurements at a low cost. Moreover, performance measures need to be periodically reviewed to check for their continued relevance (Bourne et al., 2000), and so their number needs to be small enough so that their contribution can be assessed.

Stricker et al. (2017) clearly state that the main challenge in designing KPIs consists in carefully selecting measures: on the one hand, enough KPIs must be selected for a sufficiently high information content; on the other hand, the cognitive abilities of users should not to be overstrained by selecting too many KPIs. They noted, though, that in corporate practice, the selection of KPIs is often undertaken emphasising historical usage and the implicit knowledge of decision-makers, rather than on the basis of transparent mechanisms clearly outlining benefits to users. Hence, objective scientific approaches supporting the selection process of KPIs are beneficial for managerial practice, both in an *ex-ante* (in the phase of construction of a performance measurement system) and in an *ex-post* (once it already exists and needs appropriate revisions) fashion. In order to deepen the literature related to the approaches for reducing the number of KPIs, a Scopus search was carried out. The search criterion was "Key Performance Indicator" and one of {"Reduc*", "Select*"}. The abstracts of the 2,271 papers meeting the criterion were analysed. A large majority of the papers were not relevant as the reduction or the selection was not referring to the set of KPIs, but to their use, e.g. in reducing cost. The papers that considered reducing the number of KPIs were predominantly focused on Multi-Criteria Decision-Making approaches, such as Analytic Hierarchy Process (and its variants) (Carlucci, 2010; Podgórski, 2015; Kumar and Garg, 2017), Delphi (Li et al., 2020) and ELECTRE (Gonçalves et al., 2015). Some contributions based on linear programming (Liebetruth and Otto, 2006) were found. However, such approaches do not address the issue of interdependences and redundancies among KPIs, but rely on expert judgement to drive the selection and the structuring of KPI systems. A rare exception to these approaches was Sanchez-Marquez et al. (2020) where PCA was used to select a subset of the KPIs. However, the appropriateness of the reduction was viewed in terms of the PCA measures rather than an independent measure of the information that the full and reduced KPI sets contain. As mentioned by Stricker et al. (2017), the literature does not seem to consider the need to balance a sufficiently large information content and the mental overload of decision-makers; this issue is mainly addressed at a qualitative and discursive level. Furthermore, studies seem not to mention in an explicit manner problems arising when there is a need to analyse and streamline existing sets of KPIs.

In this work, we aim to fill this gap by proposing an approach that, with the reference to an initial set of KPIs, allows the extraction of the most effective subset of KPIs that are able to retain the informative level initially captured (time period by time period variation) while reducing at the same time the interdependencies and redundancies between the KPIs. This involves two stages, firstly using PCA to reduce the KPIs, and secondly checking the performance of the reduced number of KPIs using TOPSIS. Therefore, how TOPSIS has been applied in analogous situations was investigated by Scopus searches on "TOPSIS" and "Key Performance Indicator" (giving 21 records), "TOPSIS" and "Principal Component Analysis" (giving 111 records), and "TOPSIS" and either "dimension reduction" or "size reduction" (giving 4 records). Nothing matching the motivating company problem highlighted in the Introduction was found. Generally, TOPSIS was used to rank alternatives, e.g. projects, so that the highest ranking ones could be chosen, see for example Mohammed et al. (2019). The closest matches to the approach described in Section 3 were provided by the work of Jiang (2013) and Forghani et al. (2018), where TOPSIS was employed for ranking alternatives after a set of reduced criteria had been obtained through the application of PCA. However, the use of TOPSIS as a way to evaluate the appropriateness of the data reduction effort deriving from the application of PCA, is a novelty. A key feature of the problem is that unlike, for example, using TOPSIS to rank a set of companies at a point in time based on their performance measures as in Hsu (2013), the KPIs are time series. Hence TOPSIS is used to assess how the reduced data set has captured the main fluctuations present in these time series.

The next section illustrates the proposed methods for achieving the objectives of the paper.

3. Methodology

There are two stages to the approach. Firstly, PCA is used to reduce the full set of KPIs to a smaller set of the most important ones. Secondly, how well the time series information provided by the full set of KPIs is captured by this smaller set of KPIs, is assessed using TOPSIS.

3.1 Reducing the Volume of Data: Principal Components Analysis

The main aim of the procedure presented in this study is to reduce the volume of existing data related to performance indicators, so as to obtain a more manageable set of measures.

Principal Components Analysis (PCA) is a multivariate technique. Starting from a set of correlated variables $C=\{c_1, c_2, .., c_n\}$, PCA seeks to build a new set of uncorrelated artificial variables $U=\{u_1, u_2, .., u_n\}$. These artificial variables, known as principal components, are obtained as linear combinations of the original variables, with the objective of obtaining a limited subset of components that are capable of explaining a large quota of the variance of the original dataset. This is useful for identifying redundant variables that can be removed, therefore reducing the level of complexity. For this reason, PCA seems particularly suitable to the research aims of this study. PCA will transform the original correlated indicators into a set of new uncorrelated and orthogonal variables, preserving the maximum possible proportion of variation in the data set.

Considering the set C of n indicators, the n principal components u_k (k=1, .., n) can be defined as:

$$u_k = b_{k1}c_1 + \dots + b_{kj}c_j + \dots + b_{kn}c_n$$

The generic weight b_{kj} represents the influence of indicator j on the component k. In particular, weights b_{kj} are "optimally" calculated through appropriate algorithms in order to maximise the amount of variance explained through a limited number of components and minimise the correlation within the component themselves (Kim and Mueller, 1978). The objective is to produce the set of components that can better describe the observed variables, for the given set of data (for a more detailed explanation, see Stevens, 2002). Extracted components can be then ranked in descending order, according to the amount of the total variance explained (Bruno et al., 2010).

In order to choose a significant subset U' of the principal components u_k, many rules can be used. Various methods have been put forward (and are used) for deciding how many principal components should be retained in a model, see for example Jolliffe (1986) and Krzanowski and Marriott (1994). Common ones are to use: a 'scree plot' of the eigenvalues looking for an 'elbow' after which the graph drops much more slowly; the 'eigenvalue criterion', which requires that a component's associated eigenvalue is at least 1; the 'cumulative percentage' threshold of the total variation from summing over the largest eigenvalues and to set a threshold of say 80% or 90% (for detailed explanations, see Jolliffe, 1986; OECD, 2008). Although widely used, the element of subjectivity in the 'scree plot' and 'cumulative percentage' approaches, led to the 'eigenvalue criterion' being the primary approach adopted for choosing the principal components to retain in this research.

It must be highlighted that, as principal components are linear combinations of the original indicators, they just represent artificial variables, which might lack physical meaning. As such, their usage does not represent, by itself, a practical reduction in terms of the number of physical indicators. For this reason, a correlation matrix $R=\{r_{ik}\}$ between each indicator i ($i=1 \ldots n$) and each selected component k ($k=1 \ldots p$) is calculated. Several alternatives for defining which of the variables comprise the most important ones in PCA, have been put forward (Jolliffe 1986). The approach chosen was to "*associate one variable with each of the first selected p Principal Components, namely the variable not already chosen, with the highest coefficient, in absolute value, in each successive Principal Component*" (Jolliffe 1986, p. 108) as this was one of the methods that Jolliffe (1972 and 1973) found to give reasonable subsets most of the time. In this way, we identify the subset of indicators with the highest values of r_{ik} for each $k \in U'$. These indicators can be seen as "core" indicators, as their usage (opposed to the usage of the whole set of original variables) can still explain a very significant amount of variance. However, Krzanowski and Marriott (1994, page 84) note that "*any subset that adequately represents the data and is easier to interpret than the principal components based on the full set, is worth considering*".

3.2 Evaluating the Effectiveness of the Selected Subset

The focus of this research is on the situation where the full set of performance measures have been chosen after an extensive internal consultation process by a company as being key measures of their Supply Chain Management performance. However, this process did not prescribe the combining of these measures into a single performance value, i.e. a number of important measures have been identified but not their inter-relationships. Consequently, determining how effectively the subset retains the key information contained in the full set of measures presents a very different challenge from cases in which there is a combined performance value, such as in Bruno et al. (2010). As such, the TOPSIS approach was selected to define an *ideal solution* as a combination of the full set of measures when they were each at their most positive extreme across the time horizon, and a *non-ideal solution* as the combination of the same full set of measures when they were each at their most negative extreme across the same period. For each time period, the distance of the score of these measures from these two extremes was determined. A similar calculation was performed for each time period using the reduced set of measures. Comparing these two time series showed how well the information in the reduced set of measures mirrored the information in the full set. A detailed description of this stage is given in the Appendix.

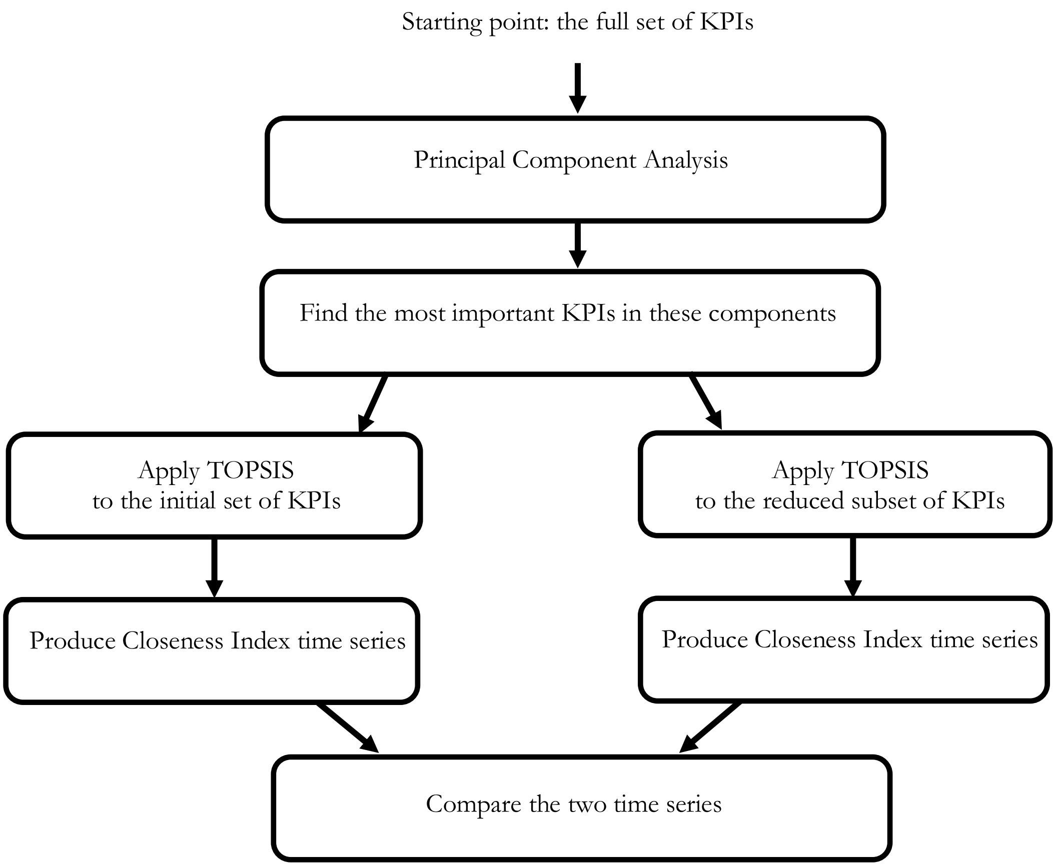

Figure 1: *The steps involved in selecting and assessing the subset of the KPIs*

4. Application of the method

The company that motivated the development of the method (see the Introduction) is used to illustrate the approach.

4.1 The Case Company and its objectives

The case company is a global automotive industry company specialising in the manufacture of high complexity aluminium components such as cylinder heads, blocks, transmissions and structural parts for over fifty customers worldwide. These are supplied by thirty-five manufacturing facilities in fifteen different countries spread across three continents. As of 2015, the company employed over 21,000 people worldwide, generating revenues of US$4.5 billion.

The company supply chain team has been working since 2010 on the development of a scorecard to analyse their performance. After a favourable local reception, this was rolled-out globally in 2015. The scorecard includes an extensive set of twenty-eight base indicators such as purchasing volume, number of active suppliers, inventory value and delayed accounts payable, covering the four areas of purchasing, warehouse, logistics and finance. These 28 indicators (shown in Table 1) were collected at all of the locations. The scorecard is intended to offer a comprehensive set of up to date information from the components of the supply chain that have been identified as being relevant, and to be accessible through the internal Enterprise Resource Planning (ERP) system. The majority of the KPIs are calculated automatically from data extracted from the ERP, but there are a few that are computed from internal inputs by a designated authorised individual.

One of the current goals of the company is the comparison of performances between locations. However, the relatively large number of indicators used in the scorecard means that it is hard to get a clear understanding of the overall relevance of the contribution from each one.

Therefore, the company identified a need for

> *"A reduced set of extremely relevant information that tells us how and what we do locally and regionally to allow immediate decisions to be taken that makes sense to global business".*

Hence, the aim was to form a subset of the 28 performance measures that provided most of the information contained in the full set of 28 measures, i.e. the subset should be efficient and effective (Jollands et al. 2004, Bruno et al. 2010) – efficient as the performance information is represented without redundancy, and effective as the subset provides sufficient information for determining where the overall performance identifies that an intervention is needed.

Table 1: Original KPIs utilised by the case company.

ID	Indicator	Description	Example Value (monthly basis)
c01	Purchasing volume	Purchase volumes (excluding Inter Company purchases)	$106,478,637
c02	Invoice values	Total Invoice values	$105,241,328
c03	Headcount of purchasing staff	Number of employees working in the purchasing function	33
c04	Purchasing volume per employee	Average purchasing volume per employee	3,226,625
c05	Invoice value per employee	Average invoicing volume per employee	3,189,131
c06	Total Purchase Orders	Quantity of Purchase Orders	7,243
c07	No. of total Purchase Orders per employee	Average Purchase Orders per employee	220
c08	No. of active suppliers	No. of active supplier with positive invoice value	856
c09	No. of coded parts	No. of registered parts on the ERP system at the end of the current month	23,289
c10	Certified Savings	Total amount of certified savings at the end of the current month	1,220,433
c11	Certified Savings per Employee	Certified Savings per employee (determined as KPI 10 divided by KPI 03)	$36,983
c12	Framework contracts	Percentage of purchases happening through Framework contracts over total purchases	44.44%
c13	Automatic Ordering	Percentage of purchases happening through automatic ordering over total purchases	32.71%
c14	Aging of open requisitions	Average days of open requisitions not transformed in a Purchase Order	6.64
c15	Total Requisition items	Total requisition items	6,851
c16	No. of emergency Purchase Orders	Quantity of Purchase Orders classified as “urgent”	250
c17	No. of single source supplier	No. of supplier being classified as unique source for specific category/material/services	145
c18	Average days for payment to vendors	Average days between purchase order and issuing of a payment to suppliers	73.45
c19	Average days of delays in payments	Average days of delays in payments to suppliers	35.34
c20	Accounts payable	Total amount of payable accounts (marked as “on time”)	$193,125,267
c21	Delayed accounts payable	Total amount of payable accounts (marked as “delayed”)	$46,338,484
c22	Inventory Value	Stock inventory value excluding raw materials, just including finished and semi-finished goods	$23,859,859
c23	Non Moving Inventory Value	Value of non-moving inventory (12 month without movement)	$7,655,908
c24	Consignment Inventory Value	Value of inventories under supplier’s property (consignment stock)	$2,874,085
c25	Inventory turnover rate	Inventory turnover rate (obtained dividing Purchase volume / average inventory value)	4.47
c26	Fill Rate	Purchase Order lines delivered with planned quantity (i.e., with all Purchase Order lines delivered) against total lines	87.03%
c27	On time delivery	Purchase Order Lines that were delivered within the planned time.	62.18%
c28	Longest Response time	Delivery status (in days) of the longest overdue purchase order	1,245

4.2 Selection step (PCA)

The observations used to illustrate the approach for reducing the number of performance measures were the weekly values of the 28 measures for the forty-two months from January 2013 to June 2016[1]. Figures 2.a and 2.b show the radar charts of the 28 variables for each of the 42 months (considering aggregated monthly values). Figure 2.a displays the yearly changes for January to June, while Figure 2.b covers the months July to December. The lengths for each measure have been standardised to lie between 0 and 1 so as to make them visually comparable. It is noticeable that the month to month patterns are more similar than those for the same month across the years; this seems to exclude cyclical and seasonal variations. The high level of variance over the 42 months indicates that there are a number of factors being measured by the performance indicators.

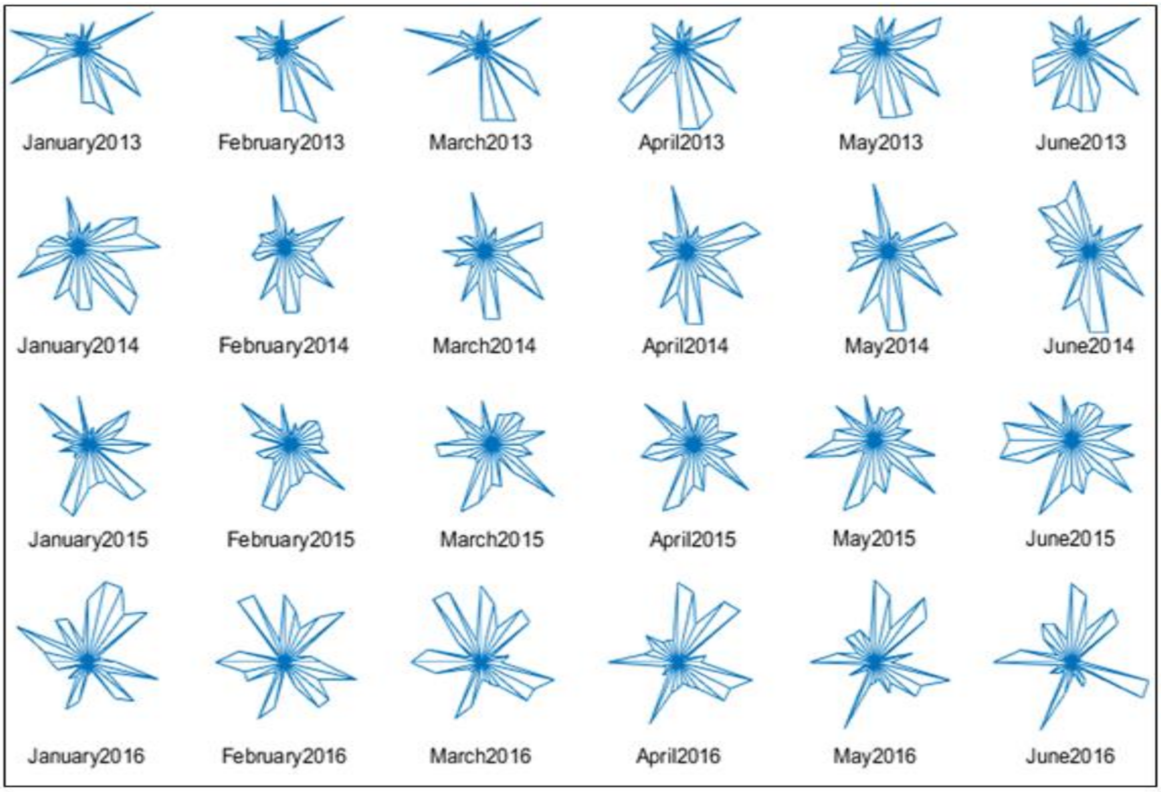

Figure 2.a: Radar charts of the 28 performance measures for each of the January to June months during the observation period

[1] PCA was run by utilising weekly values in order to rely upon a number of observations (182 weeks related to the considered 42 months) much larger than the number of considered variables (28). For ease of reporting, though, in the rest of the paper, measures are considered on a monthly horizon.

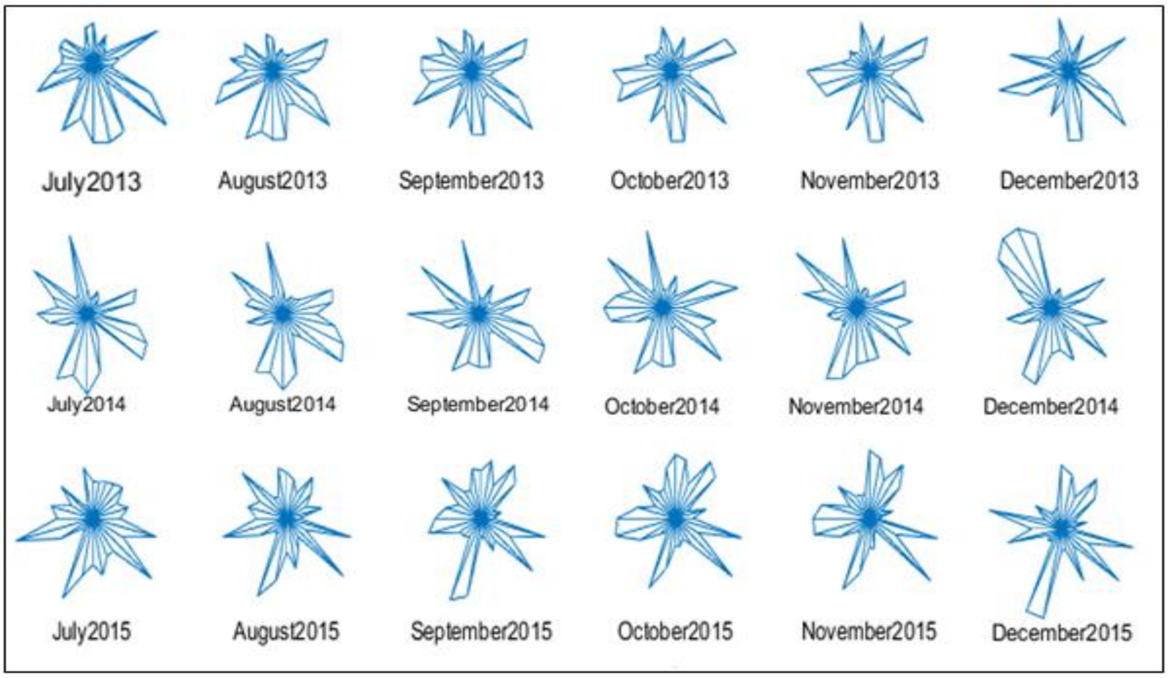

Figure 2.b: Radar charts of the 28 performance measures for each of the July to December months during the observation period

The results of the PCA are shown in Table 2. The 'eigenvalue criterion' suggests using the first 8 principle components as the reduced set. Although there is no clear breakdown point when the values in Table 2 are plotted as a scree chart (Figure 3), the 90% cumulative percentage variance threshold falls between components 8 and 9, and there is a relatively large gap in going from the 8th eigenvalue of 1.2 to the 9th eigenvalue of 0.7 (see also Figure 4). Hence, both the 'scree plot' and the 'cumulative percentage' criteria also suggest using the first 8 principal components, and so these were used as the basis of the subset. As such, the results from the PCA show that the complete set of information can be reduced from the initial twenty-eight indicators to eight components that explain over 88% of the variance.

The next stage was to select the 8 performance measures that best model these 8 components. Following on from the discussion in the methodology section (3.1), the components were taken in order of importance and for each component, the measure with the highest absolute coefficient that had not already been selected, was selected. The original set of indicators was correlated to the extracted eigenvectors of the components to formulate an interpretation based on the loadings, based on an approach similar to Kaiser's (Jackson, 1993), where the highest factor loading from the extracted component better represents the respective correlated KPI. The results are shown in Table 3, where the selected KPIs have been shaded. It can be noticed, for example, that the indicator c_7 ("No. of total Purchase Orders per employee"), that appears in the reduced set of 8 KPIs, is characterized by high interrelationships with c_3 ("Headcount of purchasing staff"), c_4 ("Purchasing volume per employee") and c_5 ("Invoice value per employee"). This means that c_7 is able alone to capture the information provided by a larger set of indicators. Similarly, the information from c_6 ("Total Purchase Orders") is largely captured by c7 and c_{13} ("Automatic Ordering").

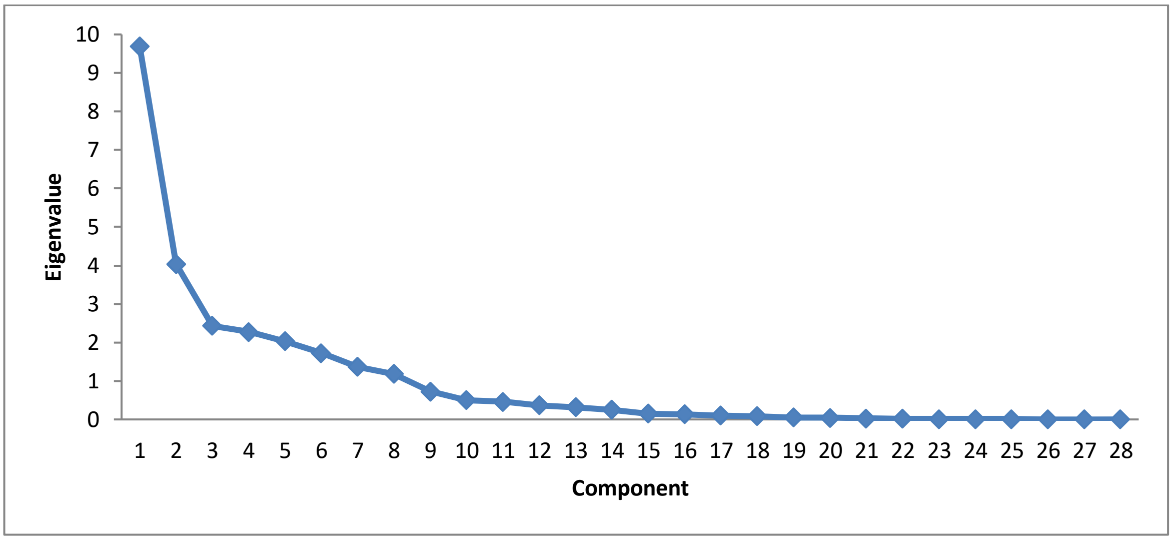

Figure 3: Scree Plot of extracted components

Table 2: The components identified by the PCA

Component	Initial Eigenvalues		
	Total	Variance (%)	Cumulative Variance (%)
u1	**9.7**	**34.6**	**34.6**
u2	**4.0**	**14.4**	**49.0**
u3	**2.4**	**8.7**	**57.7**
u4	**2.3**	**8.1**	**65.8**
u5	**2.0**	**7.3**	**73.1**
u6	**1.7**	**6.2**	**79.2**
u7	**1.4**	**4.9**	**84.1**
u8	**1.2**	**4.2**	**88.3**
u9	0.7	2.6	90.9
u10	0.5	1.8	92.7
u11	0.5	1.6	94.3
u12	0.4	1.3	95.6
…	…	…	…
u26	0.0	0.0	100.0
u27	0.0	0.0	100.0
u28	0.0	0.0	100.0

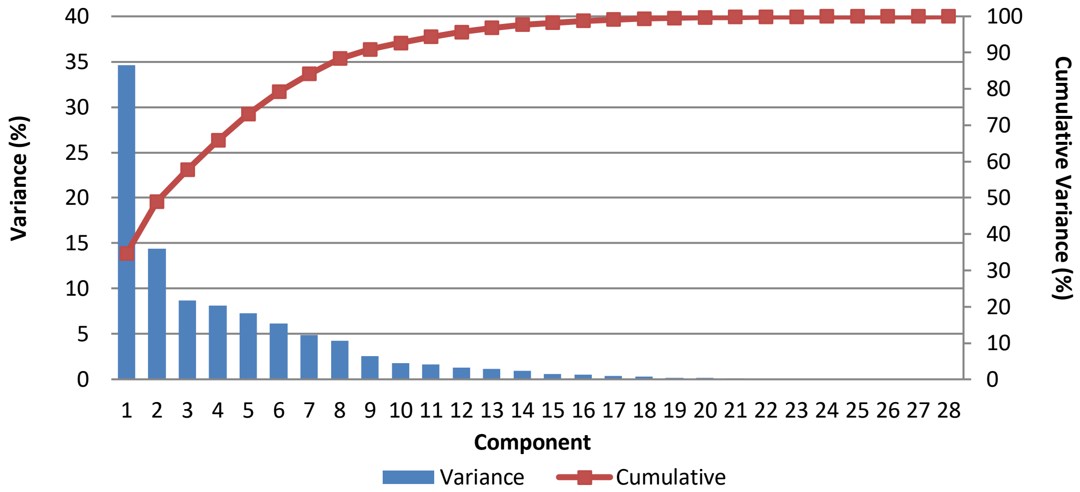

Figure 4: The variance and cumulative variance explained by the extracted components

Table 3: Factor loadings of original performance indicators on the eight extracted principal components.

Indicator		Principal Component							
		u1	u2	u3	u4	u5	u6	u7	u8
Purchasing volume	c01	-.065	.221	.768	-.398	.317	-.171	-.128	-.007
Invoice values	c02	-.411	**.467**	.315	.252	.178	.428	.001	.101
Headcount of purchasing staff	c03	**-.934**	-.117	.132	.175	.061	-.134	.101	.057
Purchasing volume per employee	c04	**.921**	-.031	.185	-.228	.161	.003	-.073	-.068
Invoice value per employee	c05	**.954**	-.053	-.078	-.047	.004	.179	-.109	-.073
Total Purchase Orders	c06	**.617**	-.100	.047	.062	.285	.266	.611	-.085
No. of total Purchase Orders per employee	c07	.962	-.136	-.087	-.048	.084	.102	.052	-.126
No. of active suppliers	c08	**.790**	-.448	-.020	.173	.093	.083	-.074	-.055
No. of coded parts	c09	-.289	**.793**	.129	.428	.040	-.108	.014	-.030
Certified Savings	c10	.577	.000	.073	.332	.055	-.461	.204	.529
Certified Savings per Employee	c11	**.613**	-.049	.051	.306	.056	-.477	.202	.499
Framework contracts	c12	-.034	**.704**	-.440	.190	-.081	-.141	-.125	-.113
Automatic Ordering	c13	-.072	.313	-.217	.001	.437	-.231	.645	-.350
Aging of open requisitions	c14	.210	-.327	-.043	-.092	**-.647**	-.087	.165	-.071
Total Requisition items	c15	.569	-.083	.193	.386	.147	.519	-.074	.128
No. of emergency Purchase Orders	c16	.034	.409	-.086	-.319	-.425	**.447**	.268	.393
No. of single source supplier	c17	**-.597**	-.366	.307	-.055	-.121	.297	.112	.336
Average days for payment to vendors	c18	-.210	-.226	-.507	-.292	.629	.138	-.103	.266
Average days of delays in payments	c19	-.261	-.050	-.571	-.228	**.589**	.137	-.118	.239
Accounts payable	c20	.470	**.725**	-.043	.095	.012	.156	-.274	.062
Delayed accounts payable	c21	.190	.808	-.233	-.188	-.085	-.194	-.179	.148
Inventory Value	c22	**-.910**	.030	.064	.267	.146	-.041	-.012	-.077
Non Moving Inventory Value	c23	**-.938**	.021	.061	.159	.089	.050	.029	-.012
Consignment Inventory Value	c24	-.483	**-.535**	-.285	-.196	-.134	-.239	-.199	.079
Inventory turnover rate	c25	.269	.186	**.710**	-.478	.278	-.171	-.097	.033
Fill Rate	c26	**-.519**	.398	-.066	-.340	-.196	.250	.306	.100
On time delivery	c27	-.089	-.269	.090	.758	.104	.169	-.177	-.014
Longest Response time	c28	**.879**	.315	-.154	.094	-.094	.049	-.044	-.017

4.3 Validation Step (TOPSIS)

The TOPSIS approach has been applied to compare the performance time series of the reduced subset of 8 KPIs to the one of the full set of 28 indicators. In both cases, the weights adopted to compute the decision matrices have been considered identical as the company evaluates all the criteria as equally important. Hence, they have been fixed equal to $\frac{1}{n}$, with n=28 and n=8 for the application to the initial and the reduced set of KPIs, respectively. Normalising the attribute weight based on the information entropy of the attribute has been suggested as an alternative to using equal weightings (Chen, 2019).

Figure 5 shows the Closeness Indices for each of the 42 months for the initial and the reduced sets of KPIs. There are 4 peaks / troughs for the Closeness Index for the full set of 28 performance measures. The first is the trough at April 2013. This was driven by the low values of a few financial measures. The peaks at June 2014 and December 2014 stemmed from maintenance periods for Original Equipment Manufacturers having a knock on effect. Finally, the peak at February and March 2016 stemmed from generally higher values across many of the measures.

For the subset of 8 performance measures, the normal level is about 0.1 below the normal level for the full set. The subset's Closeness Indices identify the peaks in the full set's Closeness Indices at June 2014, December 2014 and February-March 2016. The trough at April 2013 is missed and the drop from the February-March 2016 peak leads to a low value at April 2016.

The reasons for choosing the 8 KPIs indicated in Table 3 as the reduced set of KPIs, were reported in Section 4.2. As a further check on the efficacy of this set, a similar comparison to that of Figure 5 was carried out for 10 KPIs by adding the appropriate KPIs from the 9^{th} and 10^{th} Principal Components. These KPIs were the "Aging of open requisitions" and the "Invoice values". The results are shown in Figure 6. The results were very similar with the main difference being the overestimation of the December 2014 peak rather than the previous underestimation of this peak. Similarly, the 8 KPIs were further reduced to the set of 5 KPIs indicated in the first 5 columns of Table 3, and the results are shown in Figure 7. The fit of the reduced set of 5 KPIs is very poor. Finally, the correlation values for the Closeness Indices of these three reduced sets of KPIs when compared with the Closeness Indices from the full set of KPIs are given in Table 4. Besides Pearson's correlation coefficient, the non-parametric Kendall's tau and Spearman's rank correlation coefficients are also given. The former was calculated as it is regarded favourably by a number of authors, such as Field (2014), and the latter because of its widespread popularity. The 8 KPI set gave good correlation values for all three measures, while the 10 KPI set had weak values for Kendall's and Spearman's coefficients. The 5 KPI set gave poor correlation values for all three measures. Figure 8 illustrates the Pearson's correlation coefficient of 0.801 between the full KPI set and the 8 KPI subset. The main outlier at April 2013 is highlighted. This is the trough in the full set's index that is caused by a few financial measures. The high value at December 2014 stems from the Original Equipment Manufacturers' maintenance knock on effects, is also highlighted. The results of Figures 5 to 8 along with those in Table 4 support the choice of 8 KPIs as the 10 KPI set gives little if any extra benefit, while the 5 KPI set is inadequate.

Table 4: The correlation values between the Closeness Indices of the reduced sets of KPIs and the Closeness Indices of the full set of KPIs.

	Pearson	Kendall	Spearman
10 KPI set	0.687	0.243	0.358
8 KPI set	0.801	0.645	0.767
5 KPI set	-0.001	0.273	0.321

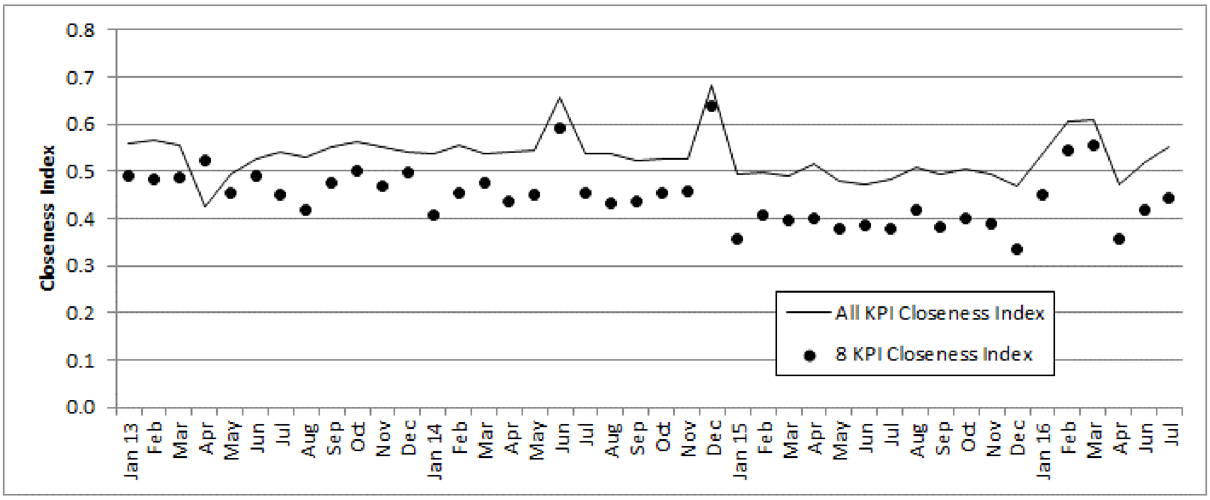

Figure 5: Comparing the Closeness Index for the full set of 28 performance indicators (the solid line) with the Closeness Index from the reduced set of 8 performance indicators (the dots).

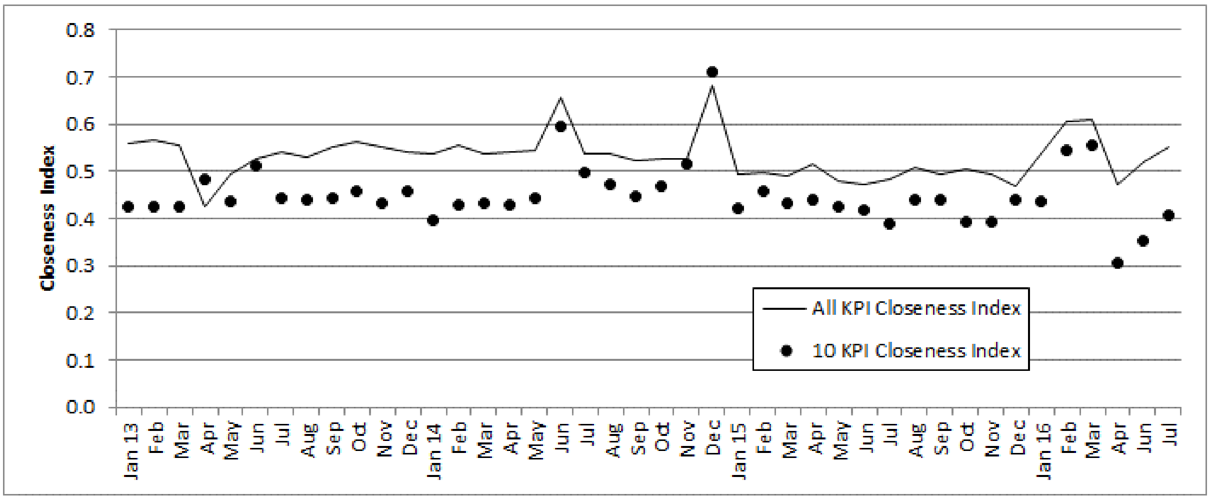

Figure 6: Comparing the Closeness Index for the full set of 28 performance indicators (the solid line) with the Closeness Index from the reduced set of 10 performance indicators (the dots).

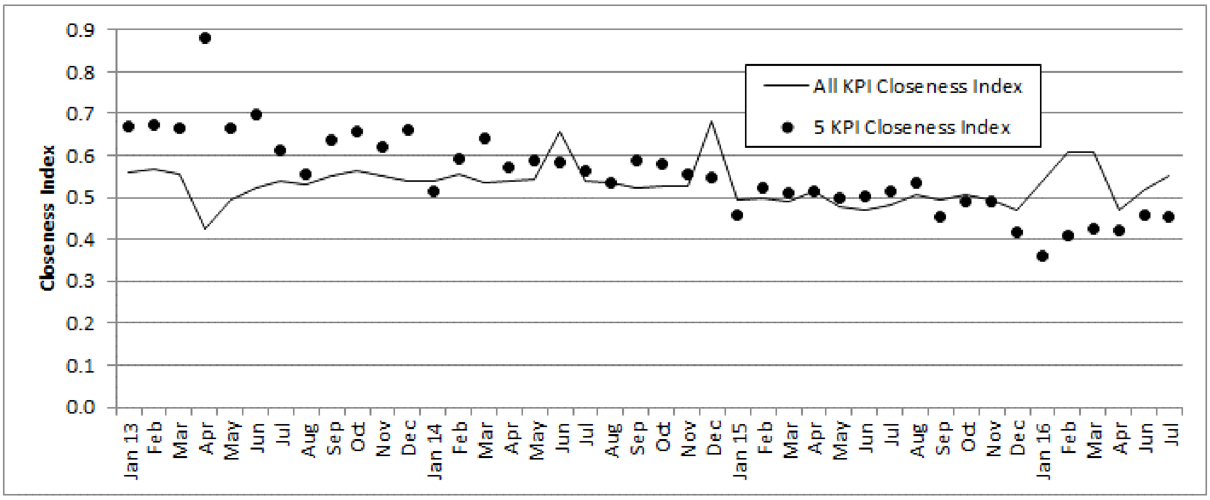

Figure 7: Comparing the Closeness Index for the full set of 28 performance indicators (the solid line) with the Closeness Index from the reduced set of 5 performance indicators (the dots).

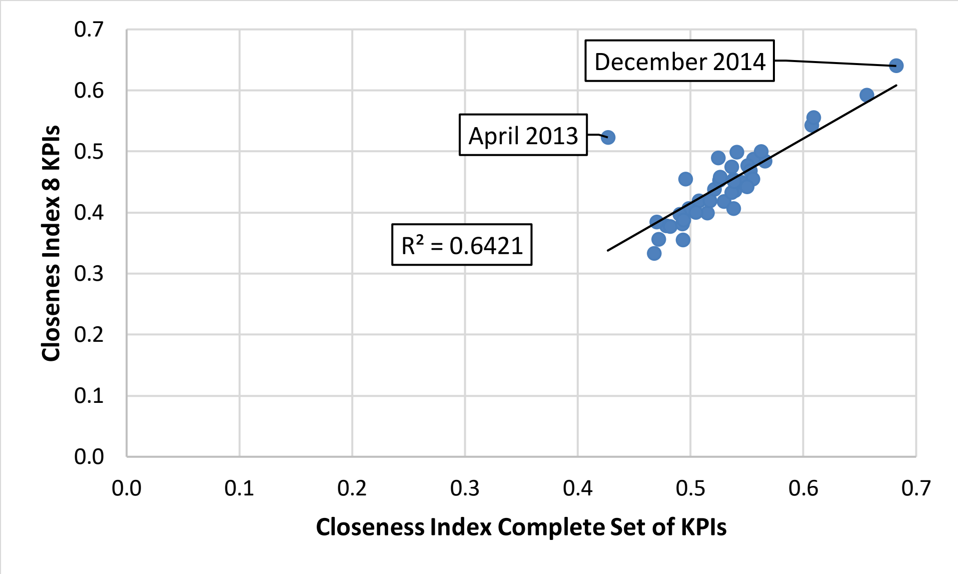

Figure 8: The Pearson correlation for the comparison of the Closeness Indices for the reduced set of 8 KPIs with the Closeness Indices of the full set of KPIs. The outlying trough at April 2013 and the high value at December 2014 are highlighted.

5 Discussion and implications

As has been described in the introductory sections of the paper, the problem faced by the case company is the number of KPIs employed in their initial implementation. The lack of knowledge of the relevance of each KPI made the current Supply Chain Management Scorecard inefficient for either prompt decision-making or a quick overview of the multiple different stakeholders or locations. This is supported by views from the Supply Chain Management literature, stating that metrics should be designed based on their relevance and importance to the decision-making process (Gunasekaran and Kobu, 2007), and in such a way to provide sufficiently high information content, while avoiding overstraining the cognitive abilities of decision-makers by selecting too many KPIs (Stricker et al., 2017). Additionally, rolling out the KPIs to countries outside of the initial implementation has the problems that different measures are recorded in different countries, and that the same measure could be recorded in different ways. Hence, there was a need to compromise between having a large number of performance indicators to capture the full picture, and having a small enough number to allow their message to be understood.

The key aspect of the case, that distinguishes it from the problems reported in the literature of Section 2, is that although the company believed that the 28 KPIs were important measures of performance, they lacked a detailed understanding of the redundancies stemming from their inter-relationships. Consequently, reduction methods such as AHP and Delphi that are based around expert opinions, were not appropriate.

Therefore, this paper has described and illustrated how an unwieldy number of KPIs can be reduced to a more practical number, and then how these can be checked to ensure that the resulting time series contain substantially the same information as the larger set's time series. Consequently, the approach reconciles the conflict between having a full picture of an organisation's performance and the need for the data requirements to be manageable.

The conducted analysis proved that a high degree of redundancy existed in the initial set of indicators, and that the adopted set of 28 KPIs was not effective in synthesising the needed information and in supporting prompt decision making. For example, the indicator c07 (included in the final set) captures a large amount of the information contained in indicators c03, c04, c05, c22 and c23, as testified by the loading factors shown in Table 3. As Figure 5 shows, the reduced set of 8 measures was able to successfully detect the peaks in the full set, but missed the trough at April 2013. Coupled with the correlation coefficient values between the two sets of respectively 0.80, 0.65 and 0.77 for Pearson's, Kendall's and Spearman's, the approach can be considered as promising. This is especially so considering the nature of the 42 months of data. As Figure 5 shows, for most months the indices exhibited little change, and when there was a peak or a trough, it usually lasted just a single month. Figure 6 shows that increasing the reduced set to 10 KPIs provides little extra information, while Figure 7 shows that reducing the number of 5 KPIs loses most of the information present in the full set of KPIs.

The proposed approach has been evaluated as particularly useful by the company in order to better support decision makers at local level and to favour the roll out of KPIs globally, at the other locations. The new set of indicators has been accepted by the company and it has been adopted without encountering significant resistance from the top management of the company, as the approach made totally clear the redundancy contained in the initial set of indicators, the inter-relationships among them and, above all, the capability of the new set of capturing all the needed information. The major benefit of this is that attention can be concentrated on understanding and managing changes in a small number of measures. As such, the company is able to allocate special attention to these indicators, to their respective results, drivers and enablers or disablers. A secondary benefit is the decrease in the data that needs to be collected.

5.1 Managerial implications

Nowadays supply chains involve high volumes of distributed resources, multiple partners and they face a high dynamicity and uncertainty of the market. In such a context, the evaluation of performance has become a complex but even more crucial issue to drive organizations towards the accomplishment of multiple, changing and conflicting objectives. While the data collection has become easier and less costly due to technological advancements and the progressive digitalization of supply chains, the process of knowledge extraction from data has become more challenging for companies. Indeed, with the increasing availability of measures on an organisation's performance and of details on a wider range of activities, it has become more difficult for managers to be able to totally understand and monitor these measures, capture their inter-relationships and to make appropriate decisions on a real-time basis. Consequently, the danger is that they end up with a large data set that is very hard to interpret. As Okoshi et al. (2019) points out, management strategy is about using knowledge of the KPIs to achieve and maintain the organisation's goals, and so the KPIs and their interrelationships need to be understood.

In order to exploit the potential of data, companies need to employ automatic and semi-automatic approaches for knowledge extraction that support them in identifying crucial data, and then synthesising and visualizing them in the most appropriate way. From a scientific point of view, this has stimulated a flourishing literature on the development of methodologies and tools for knowledge extraction to support managerial decisions (i.e., machine and deep learning techniques, statistical approaches). The approach introduced in this work allows companies to select the most effective sets of KPIs for the specific scope of the analysis.

The searches performed in Section 2 showed that the reported methods of KPI reduction are centred on managers making subjective judgements about the impact of individual KPIs. The objective statistical approach described in this paper reduces the original set of KPIs to a more manageable number and then uses TOPSIS to check that there is no major loss of information resulting from this reduction. Therefore, this two stage process provides a managers with a way of tackling the conflict between the large numbers of performance measures that information systems can provide and managers being able to understand the importance of individual KPIs so that their values can impact on management strategy.

6 Conclusions

A major direction in Operations and Supply Chain Management over the last few years has been the collection and analysis of increasing amounts of data. The hope has been that collecting evermore data and then employing data analytics, would provide organisations with insights that would be commercially advantageous. Several large industrial organisations have launched Big Data programmes to deal with the increasing complexity of global supply chains and the requirement to measure performance across a wider set of dimensions (such as the ones linked to environmental and social sustainability).

However, when monitoring an organisation's performance, the potential benefits from gathering large amounts of data need to be offset against the difficulty for managers to interpret the high dimensionality of the results. Therefore, the effectiveness of the measurement efforts can be enhanced by the careful selection of a set of KPIs, which can provide a useful way to prioritise organisational values and goals.

In this paper, a procedure for reducing a set of KPIs into a much smaller subset has been described. In particular, PCA was performed on the complete set of primary information obtained from the case company in order to reduce the volume of existing data related to performance indicators, so as to obtain a more manageable set of measures. A novel approach using the aggregation method TOPSIS (Hwang and Yoon, 1981) was employed to compare the performances from the original and reduced set of indicators, and aiming to validate the solution from the PCA. The results not only confirm the validity and efficiency of the proposal, but also present a high level of correlation (Pearson's, Kendall and Spearman's) between both sets. This process validated the proposed solution and confirmed the hypothesis that a reduced set of indicators can provide enough information from an operational and strategic perspective. The approach is important as there is a dearth of work on how to automatically reduce the number of KPIs to a more manageable number when there is no formula to produce a single performance score. This is despite the fact that the importance of having a more manageable number of performance indicators is widely accepted (Brown, 1996; Stricker et al., 2017).

The contribution of the paper has been twofold. On the one hand, the combination of the methods used in the paper has allowed a better estimate of the effectiveness of the data reduction exercise; on the other hand, the paper has tested the approach on a real world example, which, in turn, provided the overarching motivation of the research.

The main limitation of the work was its application to a single case company; further studies on other data sets would be valuable. In particular, comparative studies would allow the deriving of a set of core KPIs that could provide a useful benchmark within specific industrial sectors. Also, studies aimed at exploring the dynamic nature of KPIs, their evolution over time and their overall capability to signal detrimental time-varying phenomena happening in supply chains (i.e. bullwhip effect, ripple effect, and lumpy orders) could be performed. Specific studies could also be devoted to the evaluation of the sustainability performance of supply chains.

Appendix: The TOPSIS stage

Given its natural suitability to such scenarios, the TOPSIS method was used as the basis for calculating the distance measure from the ideal and non-ideal solutions. Indeed, the basic concept of this method is that the selected alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution in a geometrical sense (Lai et al., 1994). TOPSIS has become a highly utilised technique in multiple-criteria decision making problems (Behzadian (2012) reports 266 papers since 2000). Its steps can be summarised as follows. Assuming that x_{ij} is the score of option i, i.e. a time period, with respect to criterion j, i.e. a performance measure, then an m×n matrix, $X=(x_{ij})$, is formed. J identifies the set of positive attributes or measures, i.e. the higher the values of these measures the better, while J' identifies the set of negative attributes or measures, i.e. the lower the values of these measures the better.

- The first step consists in developing a normalised m×n decision matrix $D=(d_{ij})$, in such a way that the sum of the squared normalised values for each measure is equal to one. This step transforms various attribute dimensions into non-dimensional attributes, which allows comparisons across measures, according to the following formula:

$$d_{ij} = \frac{x_{ij}}{\sqrt{\sum_i x_{ij}^2}} \; \forall i = 1, \dots m, \forall j = 1, \dots n$$

- Assuming a set of weights for each measure (w_j for j = 1,…n), each column of the normalised decision matrix needs to be multiplied by its associated weight, in such a way to obtain a new matrix whose generic element is: $v_{ij} = w_j \, d_{ij}$

- An *Ideal Solution* can be determined as: $A^*=\{ v_1^*,\dots, v_n^*\}$, where $v_j^*=\{\max_i(v_{ij})$ if $j\in J$; $\min_i(v_{ij})$ if $j \in J'\}$. A *Negative Ideal Solution* can be determined as: $A'=\{ v_1', \dots, v_n' \}$, where $v_j' =\{\min_i(v_{ij})$ if $j\in J$; $\max_i(v_{ij})$ if $j\in J'\}$. The Ideal Solution vector is made up of the maximum values for measures that have a positive impact and the minimum values for measures that have a negative impact. The Non-Ideal Solution vector is similarly defined but with the maximums and minimums the other way around.

- The Euclidean metric is then used to find the distances the vector of normalised measures for a particular time period were away from the Ideal and Non-Ideal Solutions. In practice, the distance from the Ideal Solution can be computed as $S_i^*=[\Sigma_j (v_j^* - v_{ij})^2]^{½}$ (for each i= 1,…, m); the distance from the Negative Ideal Solution as: $S'_i =[\Sigma_j (v_j' - v_{ij})^2]^{½}$ (for each i = 1, …, m)

- Finally, a Closeness Index can be computed as $C_i^* = S'_i / (S_i^* + S'_i)$, with $0 < C_i^* < 1$.

In the same way, the distance of the subset's score from the subset's extreme solutions was also determined for each time period. Finally, Kendall's and Spearman's non-parametric correlation coefficients were calculated for the relationship between the full set's and the subset's distances. High correlation values indicate that the subset is providing a similar assessment to the full set.

References

Almeida, F. & Calistru, C. (2013). The main challenges and issues of big data management. *Inernational Journal of Research Studies in Computing,* **2**(1), 11-20. DOI: 10.5861/ijrsc.2012.209

Amrina, E. & Yusof, S. M. (2011). *Key Performance Indicators for Sustainable Manufacturing Evaluation in Automotive Companies.* Singapore, Industrial Engineering and Engineering Management, 1093-1097. DOI: 10.1109/IEEM.2011.6118084

Angerhofer, B.J. & Angelides, M.C. (2006). A model and a performance measurement system for collaborative supply chains. *Decision Support Systems,* **42**, 283-301. DOI: 10.1016/j.dss.2004.12.005

Behzadian, M., Otaghsara, S.K., Yazdani, M. & Ignatius, J. (2012). A state-of-the-art survey of TOPSIS applications. *Expert Systems with Applications,* **39**(17) 13051-13069. DOI: 10.1016/j.eswa.2012.05.056

Bourne, M., Mills, J., Wilcox, M., Neely, A. & Platts, K. (2000). Designing, implementing and updating performance measurement systems. *International Journal of Operations and Production Management,* **20**(7), 754-771. DOI: 10.1108/01443570010330739

Brown, M.G. (1996). *Keeping score: Using the right metrics to drive world-class performance*. Quality Resources: New York.

Bruno, G., Esposito, E., Genovese, A. & Gwebu, K.L. (2010). A Critical Analysis of Current Indexes for Digital Divide Measurement. *The Information Society,* **27**(1), 16-28. DOI: 10.1080/01972243.2010.534364

Cai, J., Liu, X., Xiao, Z. & Liu, J. (2009). Improving supply chain performance management: A systematic approach to analyzing iterative KPI accomplishment. *Decision Support Systems,* **46**(2), 512-521. DOI: 10.1016/j.dss.2008.09.004

Carlucci, D. (2010). Evaluating and selecting key performance indicators: an ANP-based model. *Measuring Business Excellence*, **14**(2), 66-76. DOI: 10.1108/13683041011047876

Chae, B. (2009). Developing key performance indicators for supply chain: an industry perspective. *Supply Chain Management: An International Journal,* **14**(6), 422-428. DOI: 10.1108/13598540910995192

Charan, P., Shankar, R. & Baisya, R. K. (2008). Analysis of interactions among the variables of supply chain performance measurement system implementation. *Business Process Management Journal,* **14**(4), 512-529.

Chen, P. (2019). Effects of normalization on the entropy-based TOPSIS method. *Expert Systems with Applications,* **136**, 33-41. DOI: 10.1016/j.eswa.2019.06.035

Christopher, M. & Towill, D.R. (2002). Developing Market Specific Supply Chain Strategies. *The International Journal of Logistics Management,* **13**(1), 1-14. DOI: 10.1108/09574090210806324

Estampe, D., Lamouri, S., Paris, J.-L. & Brahim-Djelloul, S. (2013). A framework for analysing supply chain performance evaluation models. *International Journal of Production Economics,* **142**(2), 247-258. DOI: 10.1016/j.ijpe.2010.11.024

Fanning, K. (2016). Big Data and KPIs: A Valuable Connection. *Journal of Corporate Accounting and Finance*, **27**(3), 17-19.

Field, A. (2014). *Discovering statistics using IBM SPSS statistics*. 4th edition, Sage: Los Angeles.

Forghani, A.; Sadjadi, S.J. & Moghadam, B.F. (2018). A supplier selection model in pharmaceutical supply chain using PCA, Z-TOPSIS and MILP: A case study. *PLoS One*, **13**(8), e0201604. DOI:10.1371/journal.pone.0201604

Franceschini, F., Galetto, M. & Maisano, D. (2007). *Management by measurement: Designing key indicators and performance measurement systems*. Springer: Berlin.

Genovese, A., Acquaye, A. A., Figueroa, A., & Koh, S. L. (2017a). Sustainable supply chain management and the transition towards a circular economy: Evidence and some applications. *Omega*, **66**, 344-357.

Genovese, A., Morris, J., Piccolo, C., & Koh, S. L. (2017b). Assessing redundancies in environmental performance measures for supply chains. *Journal of Cleaner Production*, **167**, 1290-1302.

Gonçalves, C.D.F., Dias, J.A.M. & Machado, V.A.C. (2015). Multi-criteria decision methodology for selecting maintenance key performance indicators. *International Journal of Management Science and Engineering Management*, **10**(3), 215-223. DOI: 10.1080/17509653.2014.954280

Gunasekaran, A., Patel, C. & Tirtiroglu, E. (2001). Performance measures and metrics in a supply chain environment. *International Journal of Operations and Production Management,* **21**(1/2), 333-347. DOI: 10.1108/01443570110358468

Gunasekaran, A., Patel, C. & McGaughey, R.E. (2004). A framework for supply chain performance measurement. *International Journal of Production Economics,* **87**(3), 333-347. DOI: 10.1016/j.ijpe.2003.08.003

Gunasekaran, A. & Kobu, B. (2007). Performance measures and metrics in logistics and supply chain management: a review of recent literature (1995–2004) for research and applications. *International Journal of Production Research,* **45**(12), 2819-2840. DOI: 10.1080/00207540600806513

Hawkins, D.M. (2004). The problem of overfitting. *Journal of Chemical Information and Computer Science,* **44**(1), 1-12. DOI: 10.1021/ci0342472

Hsu, L.-C. (2013). Investment decision making using a combined factor analysis and and entropy-based TOPSIS model. *Journal of Business Economics and Management,* **14**(3), 448-466. DOI: 10.3846/1611699.211.633098

Jackson, D.A. (1993). Stopping rules in principal components analysis: A comparison of heuristically and statistical approaches. *Ecology,* **74**(8), 2204-2214. DOI: 10.2307/1939574

Jiang, R. (2013). An overall performance measure for vehicle retirement decision. *Chemical Engineering Transactions*, **33**, 775-780. DOI: 10.3303/CET1333130

Jollands, N., Lermit, J. & Patterson, M. (2004). Aggregate eco-efficiency indices for New Zealand: A principal components analysis. *Journal of Environmental Management,* **73**(4), 293-305. DOI: 10.1016/j.jenvman.2004.07.002

Jolliffe, I.T. (1972). Discarding variables in principal components analysis, I: Artificial data. *Applied Statistics,* **21**(2), 160-173. DOI: 10.2307/2346488

Jolliffe, I.T. (1973). Discarding variables in principal components analysis, II: Real data. *Applied Statistics,* **22**(1), 21-33. DOI: 10.2307/2346300

Jolliffe, I.T. (1986). "Principal Component Analysis" Springer: Berlin.

Katiyar, R., Kumar Barua, M. & Meena, P.L. (2015). Modelling the measures of supply chain performance in the Indian automotive industry. *Benchmarking: An International Journal,* **22**(4), 665-696. DOI: 10.1108/BIJ-09-2014-0091

Kim, J.O., & Mueller, C.W. (1978). *Introduction to factor analysis: What it is and how to do it*. Sage: London.

Krakovics, F., Leal, J.E., Mendes Jr, P. and Santos, R.L. (2008). Defining and calibrating performance indicators of a 4PL in the chemical industry in Brazil. *International Journal of Production Economics*, **115**(2), 502-514.

Krzanowski, W.J. & Marriott, F.H.C. (1994). *Multivariate analysis, part 1: Distributions, ordination and inference*. Edward Arnold: London.

Kumar, D., & Garg, C. P. (2017). Evaluating sustainable supply chain indicators using fuzzy AHP: Case of Indian automotive industry. *Benchmarking: An International Journal*, **24**(6), 1742-1766. DOI: 10.1108/BIJ-11-2015-011.

Lai, Y.-J., Liu, T.-Y. & Hwang, C.-L. (1994). TOPSIS for MODM. *European Journal of Operational Research,* **76**(1), 486-500. DOI: 10.1016/0377-2217(94)90282-8

Li, J., Wang, Q. & Zhou, H. (2020). Establishment of Key Performance Indicators for green building operations monitoring – an application to China case study. Energies, **13**, 976. DOI: 10.3390/en13040976.

Liebetruth, T., & Otto, A. (2006). Ein formales Modell zur Auswahl von Kennzahlen [A formal model for selecting performance indicators]. *Controlling,* **18**(1): 13–24.

Martinez Sanchez, A. & Perez Perez, M. (2005). Supply chain flexibility and firm performance: A conceptual model and empirical study in the automotive industry. *International Journal of Operations and Production Management,* **25**(7), 681-700. DOI: 10.1108/01443570510605090

Mohammed, A., Harris, I. & Govindan, K. (2019). A hybrid MCDM-FMOO approach for sustainable supplier selection and order allocation. *International Journal of Production Economics*, **217**, 171-184.

OECD JRC, 2008. *Handbook on Constructing Composite Indicators: Methodology and User Guide*. OECD, Paris.

Okoshi, C.Y., de Lima, E.P. and Da Costa, S.E.G. (2019). Performance cause and effect studies: Analyzing high performance manufacturing companies. *International Journal of Production Economics*, **210**, 27-41.

Olugu, EU., Wong, KW & Shaharoun, AW.(2011). Development of key performance measures for the automobile green supply chain. *Resources, Conservation and Recycling,* **55**(6), 567-579. DOI: 10.1016/j.resconrec.2010.06.003

Podgórski, D. (2015). Measuring Operational Performance of OSH Management System – A Demonstration of AHP-based Selection of Leading Key Performance Indicators. *Safety Science* **73**: 146-166. DOI: 10.1016/j.ssci.2014.11.018.

Saad, M. & Patel, B. (2006). An investigation of supply chain performance measurement in the Indian automotive sector. *Benchmarking: An International Journal,* **13**(1/2), 36-53. DOI: 10.1108/14635770610644565

Sanchez-Marquez, R., Albarracín Guillem, J.M.; Vicens-Salort, E. & Jabaloyes Vivas, J. (2020). *Cogent Business & Management*, **7**(1), 1720944. DOI: 10.1080/23311975.2020.1720944

Scannell, T.V., Vickerey, S.K. & Dröge, C.L. (2000). Upstream supply chain management and competitive performance in the automotive supply industry. *Journal of Business Logistics,* **21**(1), 23-48. DOI: 10.1108/14635770610644565

Schmitz, J. & Platts, K. (2004). Supplier logistics performance measurement: Indications from a study in the automotive industry. *International Journal of Production Economics,* **89**(2), 231-243. DOI: 10.1016/S0925-5273(02)00469-3

Stevens, J.P. (2002). *Applied multivariate statistics for the social sciences*. 4th edition Lawrence Erlbaum Associates: New Jersey.

Stricker, N., Echsler Minguillon, F., & Lanza, G. (2017). Selecting key performance indicators for production with a linear programming approach. *International Journal of Production Research*, **55**(19), 5537-5549. DOI: 10.1080/00207543.2017.1287444

Taticchi, P., Garengo, P., Nudurupati, S.S., Tonelli, F. & Pasqualino, R. (2015). A review of decision-support tools and performance measurement and sustainable supply chain management. *International Journal of Production Research,* **53**(21), 6473-6494. DOI: 10.1080/00207543.2014.939239

Tavassoli, A. (2020). Benchmarking sustainability performance of organizations using a multicriteria approach with application to the Canadian market. *Chapter 5* in *Handbook of Research on Interdisciplinary Approaches to Decision Making for Sustainable Supply Chains,* Editors: A.Awashi & K.Grzybowska, IGI Global: Hershey PA, USA.