TRANSPORT
ISSN 1648-4142 / eISSN 1648-3480
Special Issue on Smart and Sustainable Transport / 2015 Volume 30(3): 312–319
doi:10.3846/16484142.2015.1081618

HOW SHOULD THE SUSTAINABILITY OF THE LOCATION OF DRY PORTS BE MEASURED? A PROPOSED METHODOLOGY USING BAYESIAN NETWORKS AND MULTI-CRITERIA DECISION ANALYSIS

Samir Awad-Núñez[1], Nicoletta González-Cancelas[2], Francisco Soler-Flores[3], Alberto Camarero-Orive[4]

[1, 2, 4]Dept of Transportation, Technical University of Madrid, Spain
[3]Dept of Mathematics and Computer Science applied to Civil and Naval Engineering, Technical University of Madrid, Spain

Submitted 30 November 2014; resubmitted 2 February 2015; accepted 3 March 2015

Abstract. The global economic structure, with its decentralized production and the consequent increase in freight traffic all over the world, creates considerable problems and challenges for the freight transport sector. This situation has led shipping to become the most suitable and cheapest way to transport goods. Thus, ports are configured as nodes with critical importance in the logistics supply chain as a link between two transport systems, sea and land. Increase in activity at seaports is producing three undesirable effects: increasing road congestion, lack of open space in port installations and a significant environmental impact on seaports. These adverse effects can be mitigated by moving part of the activity inland. Implementation of dry ports is a possible solution and would also provide an opportunity to strengthen intermodal solutions as part of an integrated and more sustainable transport chain, acting as a link between road and railway networks. In this sense, implementation of dry ports allows the separation of the links of the transport chain, thus facilitating the shortest possible routes for the lowest capacity and most polluting means of transport. Thus, the decision of where to locate a dry port demands a thorough analysis of the whole logistics supply chain, with the objective of transferring the largest volume of goods possible from road to more energy efficient means of transport, like rail or short-sea shipping, that are less harmful to the environment. However, the decision of where to locate a dry port must also ensure the sustainability of the site. Thus, the main goal of this article is to research the variables influencing the sustainability of dry port location and how this sustainability can be evaluated. With this objective, in this paper we present a methodology for assessing the sustainability of locations by the use of Multi-Criteria Decision Analysis (MCDA) and Bayesian Networks (BNs). MCDA is used as a way to establish a scoring, whilst BNs were chosen to eliminate arbitrariness in setting the weightings using a technique that allows us to prioritize each variable according to the relationships established in the set of variables. In order to determine the relationships between all the variables involved in the decision, giving us the importance of each factor and variable, we built a K2 BN algorithm. To obtain the scores of each variable, we used a complete cartography analysed by ArcGIS. Recognising that setting the most appropriate location to place a dry port is a geographical multidisciplinary problem, with significant economic, social and environmental implications, we consider 41 variables (grouped into 17 factors) which respond to this need. As a case of study, the sustainability of all of the 10 existing dry ports in Spain has been evaluated. In this set of logistics platforms, we found that the most important variables for achieving sustainability are those related to environmental protection, so the sustainability of the locations requires a great respect for the natural environment and the urban environment in which they are framed.

Keywords: dry ports; industrial location; sustainability; Delphi; Bayesian networks; multi-criteria decision analysis; geographic information systems.

Introduction

The dry port concept is based on moving intermodal terminals inland from port areas. This logistics platform is presented as a solution to the most important problems arising from the accumulation of activities in port areas: increasing road congestion, lack of open space in port installations and the significant environmental impact of seaports (Rodrigue 2006).

Connecting cargo handling from the port to a logistics centre helps achieve a better port operation, which

Corresponding author: Samir Awad-Núñez
E-mails: *samir.awad@caminos.upm.es; s.awad@alumnos.upm.es*

Taylor & Francis
Taylor & Francis Group

leads to a greater efficiency in ship operations (reduction in ship time in port) and to gains in energy efficiency in shipping and, particularly, to operational improvements such as the minimisation of fuel consumption and resulting greenhouse gas emissions (Moon, Woo 2014). It helps also to prevent traffic bottlenecks, thus decreasing road and railway emissions.

In addition, dry ports allow the separation of the various links of the transport chain. Thus, they are also presented as an opportunity to strengthen intermodal solutions as part of an integrated and more sustainable transport chain, allowing for the shortest possible routes for the lowest capacity and most polluting means of transport (Roso 2007; Regmi, Hanaoka 2013).

All these considerations suggest dry ports as a solution that provides a more sustainable logistics supply chain. However, while taking into account the sustainability of the logistics supply chain it is also necessary to ensure the sustainability of the site. The main goal of this article is to investigate the variables influencing the sustainability of dry port location and how this sustainability can be evaluated.

1. State of the Art of Factors Influencing the Location of Dry Ports

The diversity of factors involved in the location of industry has prompted economists over the last century to build models that try to explain the complexity of the real world. For Weber (1929), the main objective when deciding on the location for any industry is to reduce the transport and labour costs. Hotelling (1929) and Reilly (1931) consider the presence of competitors. Christaller (1933) adds the 'minimum demand threshold' in order for the location to be profitable. Taking this threshold into account, the best locations are close to large population centres. However, for Lösch (1954), the relationship between population size and type of industry is very important because the impacts on a big population density could lead to social problems. Smith (1979) introduces the concept of 'subtracted value', which consists of the negative externalities that must be weighed against the positive. According to Brown (2005), accessibility to and from the centres of origin and destination of the various flows should be maximised, which is achieved through the connection with the transportation and communication systems, generally located alongside transportation facilities forming hubs.

As can be seen, location problems are multi-objective problems and the implications on levels of economic growth, social welfare, environmental acceptability, accessibility and territorial conditions must all be taken into account. From the research of Pons Sánchez (2008), and incorporating the elements described above, the set of variables of this study is presented in Table 1. These 41 variables are grouped into 17 factors, which in turn correspond to 4 categories: environmental factors, economic and social factors, accessibility factors, and location factors. The variables can be considered as either a *benefit*, when a higher value is better in geographical analysis, or a *cost*, when a lower value is better.

2. Bayesian Networks and Multi-Criteria Decision Analysis: a Proposed Mixed Methodology

By triangulating different techniques, we have established a methodology for assessing the sustainability of the location of dry ports that can also be used to evaluate their overall quality.

MCDA has been extensively used to analyse situations that involve many variables, including situations involving location problems (Ho *et al.* 2010).

To reduce the arbitrariness of the weightings of the MCDA algorithm, we decided to use an Artificial Intelligence model based on BNs that establishes the relationship between the variables for a given sample gathered in Table 1.

The proposed methodology has been developed with the following tasks.

Task 1: work setting

Task 1.1. Diagnosis and State of the Art: the first step is reviewing the state of the art to identify the set of variables influencing the quality of the location of dry ports and variables on which they depend.

Task 1.2. Collection of geographic information: In this stage, geographic information of each variable is gathered and entered in the Geographic Information System ArcGIS software, used as a tool to quickly and easily access the required data from an extensive geographic database of several maps.

Task 2: building the model of artificial intelligence

In this paper, we have chosen to use BNs for their ability to represent a causal model using a graphical representation of dependencies between variables that are part of the application domain. They are based on probability theory and combine the power of Bayes' theorem with the semantic expressiveness of directed graphs. According to the type of structure of the data, different structure-learning methods can be applied. To build the BN we chose a K2 structure-learning algorithm, because it allows the variables to be ordered. This way, the network can be stratified.

Since we cannot enumerate all the possible Directed Acyclic Graphs (DAGs), for the BN structure learning, we have to try heuristic methods. Since DAGs are acyclic and the parents of the variables are before children in causal ordering, knowing the ordering of the variables can reduce the structure space. If we know a complete ordering of the nodes, finding the best structure amounts to picking the best set of parents for each node independently. This is what the K2 algorithm does.

The K2 algorithm is based on the optimization of a measure. This measure is used to explore, using the algorithm, the search space consisting of all networks that contain the variables of the dataset. It starts with an initial network and it is modified (adding or removing paths, or changing their direction) obtaining a new network with the best measure (Cooper, Herskovits 1992).

Table 1. Factors influencing the location of dry ports

Category	Factor	Factor weighting	Variable code	Variable	Kind	Variable weighting
Environmental factors	Impact on natural environment	5.00	DNS	Distance to natural spaces	Profit	10.00
			CNE	Connectivity on natural environment	Profit	0.00
			NIS	Number of isolated spaces	Cost	9.10
			DFA	Density of the facility area	Profit	0.00
	Impact on urban environment	7.25	DUS	Distance to urban spaces	Profit	8.20
			CUE	Connectivity on urban environment	Cost	8.20
	Hydrology	6.00	DSW	Distance to surface water	Profit	7.30
			FL	Flooding level	Profit	7.30
			GP	Groundwater presence	Profit	6.40
Economic and social factors	Land Price	7.00	LP	Land price	Cost	7.30
	Potential demand growth	6.40	IPI	Industrial production index	Profit	6.40
			GDP	Gross Domestic Product	Profit	5.50
			EL	Employment rate	Cost	6.40
	Hosting municipality range	5.00	PL	Population level	Profit	4.60
			PD	Population density	Cost	5.50
Accessibility factors	Accessibility to the rail network	10.00	NRA	Number of railway accesses	Profit	5.50
			IRE	Importance of the railway environment	Profit	8.20
			CD	Centrality of demand	Profit	5.50
			QR	Quality of the railway	Profit	0.00
	Accessibility to high capacity roads network	10.00	DAHCN	Direct access to the high capacity network	Profit	4.60
			DHCR	Distance to a high capacity road	Cost	3.70
			NL	Number of lanes	Profit	3.70
	Accessibility to airports	5.00	DA	Distance to an airport	Cost	5.50
	Accessibility to ports	10.00	DP	Ports nearer than 400 km	Profit	2.80
	Accessibility to supplies and services	8.00	CSS	Currency of supplies and services	Profit	0.00
Location factors	Weather	3.00	CV	Climatic variety	Profit	5.50
			RL	Rainfall level	Cost	2.80
			WF	Winter frosts	Profit	2.80
	Orography	5.00	TC	Terrain curl	Profit	5.50
			SL	Slope	Cost	2.80
	Geology	5.00	EX	Excavability	Cost	8.20
			CS	Compressive strength	Profit	8.20
	Relation with other logistics platforms	8.00	NNLP	Number of nearby logistic platforms	Cost	1.90
			NMDLP	Number of middle-distance logistic platforms	Profit	3.70
			BICA	Belonging to an industrial consolidated area	Profit	1.00
	Integration into the main supply chain infrastructures	5.50	DPFC	Distance to a principal freight corridor	Cost	5.50
	Potential optimization of the modal shift	5.05	DPPC	Distance to a principal passenger corridor	Profit	6.40
			NPT	Number of passenger trips	Cost	6.40
			NRADT	Nearest roads' ADT	Cost	1.00
			DTENT	Distance to the TEN-T core network corridors	Profit	3.70

Specifically, the K2 algorithm for a network B_S and for data set D, can be written as in Eq. (1):

$$P(B_S, D) = P(B_S)\prod_{i=1}^{n}\prod_{j=1}^{q_i}\frac{(r_i-1)!}{(N_{ij}+r_i-1)!}\prod_{k=1}^{r_i}(N_{ijk})! = P(B_S)\prod_{i=1}^{n} g(i, Pa_i), \quad (1)$$

where: N_{ijk} is the number of cases in D for which X_i(i=1, …, n) takes its k-th value when Pa_i (X_i parents in B_S) is taken in their j-th instance; q_i is the number of possible instances of all parents; r_i is the number of values that can be taken by X_i.

K2 begins by assuming that a node has no parents, so all structures are equally likely initially. The algorithm then incrementally adds the parent whose addition most increases the score of the resulting structure. For each node, the algorithm searches for the K2 parents that maximize Eq. (2):

$$g(i, Pa_i) = \prod_{j=1}^{q_i}\frac{(r_i-1)!}{(N_{ij}+r_i-1)!}\prod_{k=1}^{r_i}(N_{ijk})!. \quad (2)$$

At each step, K2 incrementally adds any parent node whose inclusion increases $g(i, Pa_i)$, when no addition of a single parent can increase the score, it stops adding parents to the node.

As can be seen, K2 is a search algorithm that optimizes the probability of the given network dataset. Actually, this algorithm finds the most likely set of parents, using a Bayesian metric, by measuring the likelihood of the structure given the input data. Its main advantage is that ordering the nodes significantly reduces the search space in comparison with other algorithms because any node, which is below another cannot be its parent. This allows the network structure to be ascertained with reasonable computational resource. Specifically, in this paper we used the K2 algorithm implementation developed in the program Elvira (Elvira Consortium 2002).

Task 3: establishment of weightings

Task 3.1. Weightings of the variables: to obtain the weighting of each variable, the factors were classified according to their strata relative to the root node of the network, and thresholds were defined based on the 'depth' of the factor within the network. Each factor is weighted according to both its importance and its depth.

Task 3.2. Weighting of the factors: these are established by applying the Delphi methodology. This technique was chosen for its ability to reach consensus in a group of experts from many different specialties (the panel included more than 60 experts from the different disciplines that come together in this research: logistics, sustainability, environmental impact, transport planning and geography), something very important in a multidisciplinary problem such as that presented in this work.

Task 4: establishment of scores based on geographic information analysis

Task 4.1. Standardised Score of geographic information: the variables are sourced from geographic information, and as such, each variable has a different range of possible values. To normalize the measures and to make all correspond to a scale from 0 to 10, we used a spline interpolation. The obtained Criteria Assessment Score, $f_k = f(x_1^i, x_2^i, n, x_j^i) = f(x_j^i)$ was normalized by using a spline:

$$P\left[f_k\left(x_j^i\right)\right] = \lambda_1\left[f_k\left(x_1^i, x_2^i, \ldots, x_j^i\right)\right]^n + \lambda_2\left[f_k\left(x_1^i, x_2^i, \ldots, x_j^i\right)\right]^{n-1} + \lambda_n f_k\left(x_1^i, x_2^i, \ldots, x_j^i\right) + \lambda_{n+1}. \quad (3)$$

Spline interpolation is often preferred over polynomial interpolation because the interpolation error can be made small even when using low degree polynomials for the spline. We used three different kinds of boundary conditions in order to obtain the different degrees of the spline (Table 2).

The kind of interpolation is selected by minimizing the distance between the Measured Criteria Assessment Score (MCAS) and the Standardised Criteria Assessment Score (SCAS), thereby reducing the interpolation error. When linear interpolation had a big error, we used quadratic interpolation (with a maximum in the highest MCAS). When this second approximation failed to reduce the error sufficiently, we used cubic interpolation, with at least two inflection points in the extremes.

Table 2. Spline interpolation boundary conditions

Interpolation	Boundary conditions
Linear	$P\left\{\max\left[f_k\left(x_j^i\right)\right]\right\} = 10$; $P\left\{\min\left[f_k\left(x_j^i\right)\right]\right\} = 0$
Quadratic	$P\left\{\max\left[f_k\left(x_j^i\right)\right]\right\} = 10$; $P\left\{\min\left[f_k\left(x_j^i\right)\right]\right\} = 0$; $P'\left\{\max\left[f_k\left(x_j^i\right)\right]\right\} = 0$
Cubic	$P\left\{\max\left[f_k\left(x_j^i\right)\right]\right\} = 10$; $P\left\{\min\left[f_k\left(x_j^i\right)\right]\right\} = 0$; $P''\left\{\max\left[f_k\left(x_j^i\right)\right]\right\} = 0$; $P''\left\{\min\left[f_k\left(x_j^i\right)\right]\right\} = 0$

Task 5: application of the linear weighted multi-criteria decision analysis algorithm

Using the weightings obtained in Task 3 and the SCAS of Task 4, and then from Eq. (4), the quality of the location of dry ports is obtained:

$$LQR_i = EP \cdot \sum \left(SCAS_{ik} \cdot w_k \right) \cdot W_{\bar{k}};$$
$$EP \in N(0,1);$$
$$i \in N(1,\ldots,10);\ k \in N(1,\ldots,17);\ \bar{k} \in N(1,\ldots,40), \qquad (4)$$

where: LQR_i (Location Quality Rate) is the ratio of the quality of each location; EP (Environmental Protection) is the dichotomous function 'Environmental Protection', which serves to exclude protected areas (worth 0 for protected locations and 1 for locations without environmental protection); $SCAS_{ik}$ (Standardised Criteria Assessment Score) is the score of the evaluation criteria for each variable and location. Finally, w_k are the weightings of each variable obtained by depth compared with the root of the BN and the $W_{\bar{k}}$ are the weightings obtained in the DELPHI questionnaire to fix the importance of each factor. The locations with a higher LQR value will be most appropriate for solving the problem.

3. Case of Study: Sustainability of the Existing Dry Ports in Spain

Spain is a country located in South-Western Europe. Its infrastructure network is established as a mesh with a substantially radial layout centred on Madrid. The country has invested heavily in a network of high speed rail for travellers, which has freed up capacity on the well-maintained conventional rail network, to transport goods from the ports to the hinterland. However, this infrastructure is underutilized (the railroad moves less than 5% of all goods in the country), partly because of poor planning.

There is also a widely held view that railway transport is the most sustainable land transport and its use should be increased (Roso *et al.* 2009). Linking these two aspects, and considering that dry ports are presented as an opportunity to strengthen intermodal solutions as part of an integrated transport chain (McCalla 2007), we decided to assess the quality of the locations of dry ports to lay the foundation to develop public policies into an overall national logistics plan focused on the railway transport and sustainability aspects.

Results and Discussion

Eq. (4) requires the following inputs: (1) the weightings of each variable and factor and (2) the SCAS of each variable and location.

Using the geographic information of the 10 existing dry ports in Spain, a K2 BN algorithm was built. The result determines the relationship between all the variables involved in the decision. The network obtained is represented in Fig. 1.

As can be seen, DNS is the root node of the whole network because no path enters it. By assessing the importance of each variable by depth compared with the root of the network, a certain weighting is set for each variable. Depth is related to the number of steps to reach DNS and the number of relationships between the evaluated variable and the other variables. Table 3 shows the results of this procedure.

The four conditionally independent variables are unrelated to the rest of the network variables. These variables have been given a weighting $w_k = 0$. This is because, in our case study, these four variables have similar values for all locations, which precludes any analysis of the quality or suitability of these variables. Therefore, they do not serve our purpose of classifying the quality of the locations.

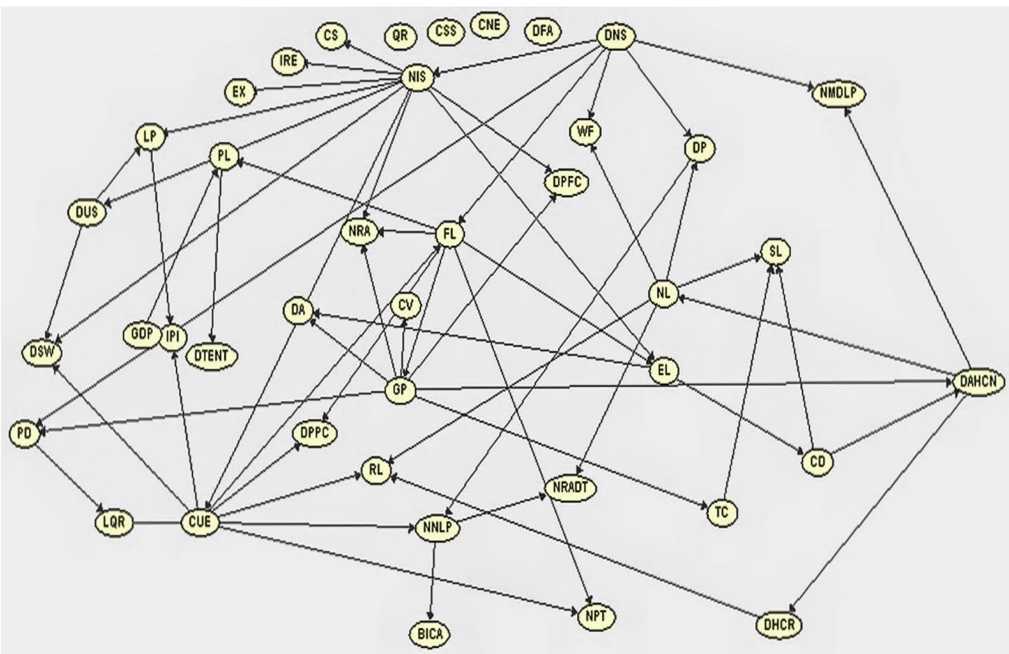

Fig. 1. K2 algorithm Bayesian Network

Table 3. Layer distribution of each variable according to depth on Bayesian Network

Layer	1	2	3	4	5	6	7	8	9	10	11	Out
Variables	DNS	NIS	DUS	DSW	GP	GDP	PL	DTENT	RL	NNLP	BICA	CNE
			CUE	FL	EL	PD	DAHCN	NMDLP	SL		NRADT	DFA
			CS	LP	IPI	DPFC	LQR	DHCR	WF			QR
			EX		DPPC	CV		NL	DP			CSS
			IRE		NPT	TC						
						NRA						
						DA						
						CD						
Weighting	10	9.1	8.2	7.3	6.4	5.5	4.6	3.7	2.8	1.9	1	0
Key		Environmental		Economic and social		Location		Accessibility		LQR		

In order to obtain the weightings of the factors we used a Delphi questionnaire. In Table 1, the weightings of each factor are compiled. Awad-Núñez *et al.* (2014) shows the survey results of the Delphi methodology. As shown in that paper, only 14 factors were employed, compared with 17 considered in this research. The weightings of the 3 additional factors were obtained through missing data analysis techniques, maintaining the weightings of the factors that are known and their importance as given by the questionnaire. It has been inferred by propagation probability, for which there are various algorithms that take advantage of independence encoded by the network to perform calculations efficiently (Nilsson 1998). The propagation of probability is used to obtain the posterior probabilities of certain network variables when the value taken by some other observed variables is known:

- What is the probability of a given value assignment for a subset of variables *Y*?
- What is the probability of different value assignments for query variables *Y* given evidence about variables *Z*?

Each network node corresponds to a discrete variable, $A=\{A_1,A_2,\ldots,A_n\}$, with its respective conditional probability matrix, $P(B|A)=P(B_j\,|\,A_i)$. Given some evidence *E* (represented by a fixed value from the questionnaire), the posterior probability of any other variable *B* is, according to Bayes' theorem, $P(B_i|E)=\dfrac{P(B_i)\cdot P(E\,|\,B_i)}{P(E)}$.

In classification, given the training data and a new example, we want to determine the most probable class label of the new example. Given a BN and a random variable *B*, deciding whether $P(B=b\,|\,E)>0$ is NP-hard. This implies that there is no general inference procedure that will work efficiently for all network configurations. However, for particular families of networks, inference can be done efficiently. In other cases, instead of exact inference (computing the probabilities exactly) we will use approximate inference (computing the probabilities with reasonable precision).

Applying Eq. (4), with the weighting from Table 1 and the SCAS from the geographic information analysis using ArcGIS (Table 4); we obtained the results compiled in Table 5.

Table 4. Compilation of Standardised Criteria Assessment Score

Variable	SCAS									
	I	II	III	IV	V	VI	VII	VIII	IX	X
DNS	1.5	0.9	2.3	10.0	5.8	2.1	2.3	0.8	4.0	6.4
CNE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
NIS	0.0	7.5	5.0	2.5	2.5	7.5	5.0	5.0	0.0	0.0
DFA	10.0	10.0	0.0	0.0	10.0	10.0	10.0	10.0	10.0	10.0
DUS	2.5	0.0	0.0	2.0	2.0	0.0	3.5	6.1	2.0	0.0
CUE	6.7	0.0	3.3	6.7	8.3	0.0	3.3	6.7	0.0	0.0
DSW	0.8	2.0	1.6	0.0	0.0	4.6	4.7	1.8	9.1	0.0
FL	10.0	0.0	5.0	0.0	10.0	10.0	0.0	10.0	0.0	5.0
GP	0.0	0.0	0.0	0.0	10.0	0.0	0.0	10.0	0.0	0.0
LP	4.7	5.5	6.5	9.2	9.2	9.0	8.8	8.4	1.5	1.5
IPI	5.3	10.0	3.5	8.0	8.0	8.0	8.0	4.5	3.1	3.1
GDP	5.8	8.6	6.1	7.6	7.6	7.6	7.6	7.1	10.0	10.0
EL	0.0	4.5	4.7	3.5	3.5	6.5	4.6	5.1	5.6	5.6
PL	10.0	0.3	10.0	1.3	0.6	10.0	1.8	5.6	10.0	10.0
PD	9.4	9.6	0.0	9.5	9.1	0.0	5.5	9.0	0.0	0.0
NRA	10.0	3.0	8.0	10.0	8.0	10.0	5.0	5.0	10.0	10.0
IRE	6.0	2.0	4.0	6.0	6.0	2.0	8.0	4.0	10.0	10.0
CD	4.0	3.0	10.0	4.0	3.0	7.0	4.0	7.0	7.0	10.0
QR	10.0	10.0	10.0	10.0	5.0	10.0	10.0	5.0	10.0	10.0
DAHCN	0.0	5.0	10.0	5.0	5.0	10.0	5.0	0.0	10.0	10.0
DHCR	4.0	0.0	10.0	0.0	6.7	10.0	7.3	0.0	10.0	10.0
NL	10.0	10.0	10.0	10.0	10.0	10.0	10.0	0.0	10.0	10.0
DA	0.0	2.7	3.3	2.7	0.0	9.7	0.0	0.0	8.5	6.8
DP	8.8	8.8	2.5	8.8	10.0	6.3	6.3	8.8	2.5	2.5
CSS	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
CV	5.0	0.0	0.0	0.0	5.0	0.0	0.0	10.0	0.0	0.0
RL	4.5	6.9	5.5	2.3	3.3	4.5	5.5	0.0	5.6	5.6
WF	10.0	10.0	10.0	0.0	10.0	0.0	0.0	10.0	10.0	10.0
TC	10.0	10.0	10.0	2.0	2.0	10.0	10.0	2.0	10.0	10.0
SL	10.0	10.0	5.0	2.5	2.5	7.5	10.0	5.0	10.0	10.0
EX	6.4	0.4	0.0	8.3	0.9	0.4	0.0	0.4	10.0	8.3
CS	6.5	2.7	2.3	8.7	3.0	2.7	2.3	2.7	10.0	8.7

End of Table 4

Variable	SCAS									
	I	II	III	IV	V	VI	VII	VIII	IX	X
NNLP	8.0	5.0	0.0	6.0	0.0	3.0	2.0	8.0	0.0	3.0
NMDLP	2.8	5.9	10.0	7.0	7.0	10.0	6.0	5.0	10.0	10.0
BICA	5.0	10.0	10.0	5.0	5.0	10.0	5.0	5.0	10.0	10.0
DPFC	1.0	7.0	8.0	2.0	0.0	6.0	5.0	3.0	9.0	10.0
DPPC	8.6	2.9	6.4	4.7	7.3	3.7	0.0	6.7	4.6	1.7
NPT	8.9	4.0	6.6	7.8	9.1	7.9	5.5	8.7	7.2	0.0
NRADT	9.6	8.0	8.4	9.4	8.8	7.8	8.9	9.9	7.6	4.3
DTENT	10.0	5.0	10.0	10.0	5.0	0.0	10.0	10.0	10.0	10.0

Notes: I – Antequera; II – Santander-Ebro (Luceni); III – Azuqueca de Henares; IV – La Robla; V – Toral de los Vados; VI – Villafría (Burgos); VII – Venta de Baños (Ventasur); VIII – Monforte de Lemos; IX – Coslada; X – Abroñigal.

Each dry port presents a weighted score for each category: environmental, economic and social accessibility and location. Merging the results of the environmental and economic and social variables, we obtained the sustainability of each dry port. Taking into account all the full set of variables quality can be observed.

The best dry port in each category in Table 5 is highlighted in green and the worst one is highlighted in red. For easier understanding of the explanation of the results, these are gathered in Fig. 2.

The most sustainable dry port is Monforte de Lemos, which scored well in terms of social and environmental factors and was balanced in the economic section with 60.3% of the maximum possible score. Meanwhile, the least sustainable locations are Coslada, Abroñigal and Santander-Ebro – all of them with low social and environmental scores that are not compensated by the economic section.

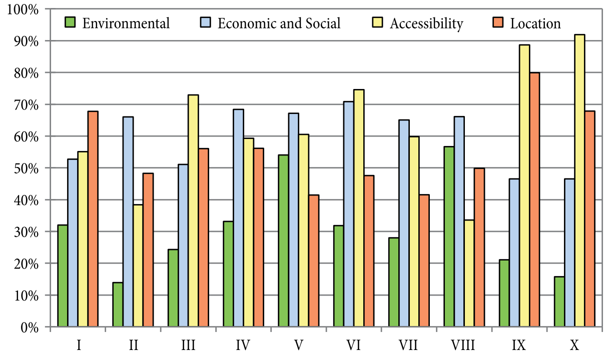

Fig. 2. Bar chart gathering the main results

For its part Coslada has the best quality location if all the variables are taken into account, with 57.2%.

These modest results show that both sustainability and quality of dry port locations in Spain is moderate. This can also be seen in the median values, of 41.3% and 48.8% respectively.

Analysing sustainability, scores in economic and social variables are much better than in environmental variables. As environmental variables, appear to be the ones with the biggest weightings. this produces moderate sustainability ratings. In addition, the set of sustainability assessments of the locations has a standard deviation of 11.1%, so it can be considered that the quality of the locations is grouped around the central values.

By looking at the overall quality of the locations (taking into account LQR value), we saw that dry ports have higher grades than 60% in accessibility and higher than 50% in location. However, as was the case for sustainability, these ratings are not able to pull up the overall rating because the environmental variables are the most weighted of the model. Again, we can say that there is little dispersion in the sample, in this case with a standard deviation of 6%.

Table 5. MCDA algorithm results

	Environmental		Economic and social		Accessibility		Location		Sustainability		Quality (LQR)	
I	1091.2	32.1%	1152.8	52.7%	2025.0	55.1%	2224.2	67.8%	2244.1	40.1%	6022.0	48.0%
II	474.3	13.9%	1444.5	66.0%	1412.2	38.4%	1583.6	48.2%	1918.8	34.3%	4827.0	38.5%
III	827.5	24.3%	1116.3	51.0%	2679.9	72.9%	1839.0	56.0%	1943.8	34.8%	6174.5	49.2%
IV	1129.0	33.2%	1495.5	68.4%	2180.2	59.3%	1841.8	56.1%	2624.5	46.9%	6646.5	53.0%
V	1841.0	54.1%	1469.8	67.2%	2223.7	60.5%	1359.4	41.4%	3310.8	59.2%	6071.8	48.4%
VI	1085.3	31.9%	1548.9	70.8%	2741.3	74.6%	1561.6	47.6%	2634.1	47.1%	6297.6	50.2%
VII	953.2	28.0%	1423.9	65.1%	2197.3	59.8%	1363.8	41.6%	2377.2	42.5%	5732.5	45.7%
VIII	1928.2	56.6%	1445.4	66.1%	1233.0	33.6%	1635.4	49.8%	3373.6	60.3%	5341.2	42.6%
IX	719.2	21.1%	1017.7	46.5%	3257.7	88.6%	2622.8	79.9%	1737.0	31.1%	7217.0	57.5%
X	537.2	15.8%	1017.7	46.5%	3377.0	91.9%	2228.2	67.9%	1554.9	27.8%	6941.1	55.3%
Average	1058.6	31.1%	1313.3	60.0%	2332.7	63.5%	1826.0	55.6%	2371.9	42.4%	6127.1	48.8%
Median	1019.3	29.9%	1434.2	65.6%	2210.5	60.1%	1737.2	52.9%	2310.6	41.3%	6123.2	48.8%
Std Dev	373.2	11.0%	338.3	15.5%	662.2	18.0%	561.5	17.1%	623.0	11.1%	754.4	6.0%
Max	3404.0		2187.2		3675.0		3282.3		5591.2		12548.5	

Notes: I – Antequera; II – Santander-Ebro (Luceni); III – Azuqueca de Henares; IV – La Robla; V – Toral de los Vados; VI – Villafría (Burgos); VII – Venta de Baños (Ventasur); VIII – Monforte de Lemos; IX – Coslada; X – Abroñigal.

Conclusions and Future Research

In this paper, we have tried to convey the idea that the determination of the most appropriate location to place dry ports is a geographic and multidisciplinary problem with environmental, economic, social, accessibility and location repercussions.

Although the results of the Delphi questionnaire show a greater importance in the search for the location of a dry port for the aspects considered in the classical theories of industrial location (accessibility to the rail network, accessibility to high-capacity main roads and accessibility to seaports), the Delphi weightings are corrected according to the relationships established between variables by taking into account the Bayesian weightings. Ultimately, environmental variables prove to be the most important in deciding the location. Also, although the four conditionally independent variables (Connectivity with the natural environment, Density of facility area, Quality of the railway, Currency of supplies and services) are unrelated to the rest of the network. We must not lose sight of these variables in future evaluations since new input values would vary the relationship between them and the rest of the BN.

A very important conclusion is that the satisfactory results allow us to confirm the great power of applying BNs and MCDA to the assessment of dry port location. In addition, the triangulation of different independent techniques provides greater confidence in the results, because the use of BNs and Delphi methodology reduces the arbitrariness of the weightings of the MCDA algorithm.

By implementing the MCDA algorithm into a McHarg Geographic Information System, we will be able to develop a powerful decision-making tool. Furthermore, the versatility of the model will allow with small changes in the variables, the location of other logistics platforms or NIMBY facilities other than dry ports.

References

Awad-Núñez, S.; González-Cancelas, N.; Camarero-Orive, A. 2014. Delphi methodology used for determining weighting factors influencing the location of Dry Ports, *News in Engineering* 2(2): 55–62.

Brown, N. D. 2005. *La teoría de la localización*. Universidad de Barcelona. 73 p. Available from Internet: http://riscd2.eco.ub.es/~nduch/postgrau_archivos/Duch_localizacion.pdf (in Spanish).

Christaller, W. 1933. *Central Places in Southern Germany*. Prentice Hall. 230 p.

Cooper, G. F.; Herskovits, E. 1992. A Bayesian method for the induction of probabilistic networks from data, *Machine Learning* 9(4): 309–347. http://dx.doi.org/10.1007/BF00994110

Elvira Consortium. 2002. ELVIRA: an environment for probabilistic graphical models, in J. Gámez, A. Salmerón (Eds.). *Proceedings of the First European Workshop on Probabilistic Graphical Models (PGM'02)*, 222–230.

Ho, W.; Xu, X.; Dey, P. K. 2010. Multi-criteria decision making approaches for supplier evaluation and selection: a literature review, *European Journal of Operational Research* 202(1): 16–24. http://dx.doi.org/10.1016/j.ejor.2009.05.009

Hotelling, H. 1929. Stability in competition, *The Economic Journal* 39(153): 41–57. http://dx.doi.org/10.2307/2224214

Lösch, A. 1954. *The Economics of Location*. Translated from the 2nd revised edition by W. H. Woglom, W. F. Stolper. Yale University Press. 520 p.

McCalla, R. J. 2007. Factors influencing the landward movement of containers: the cases of Halifax and Vancouver, in J. Wang, D. Olivier, T. Notteboom, B. Slack (Eds.). *Ports, Cities and Global Supply Chain*, 121–137.

Moon, D. S.-H.; Woo, J. K. 2014. The impact of port operations on efficient ship operation from both economic and environmental perspectives, *Maritime Policy & Management: the Flagship Journal of International Shipping and Port Research* 41(5): 444–461. http://dx.doi.org/10.1080/03088839.2014.931607

Nilsson, D. 1998. An efficient algorithm for finding the M most probable configurations in probabilistic expert systems, *Statistics and Computing* 8(2): 159–173. http://dx.doi.org/10.1023/A:1008990218483

Pons Sánchez, A. 2008. *Localizaciones óptimas para puertos secos*: PhD Thesis. Departamento de Infraestructura del Transporte y del Territorio, Universidad Politécnica de Cataluña, Spain. 126 p. Availabe from Internet: http://upcommons.upc.edu/handle/2099.1/5917 (in Spanish).

Regmi, M. B.; Hanaoka, S. 2013. Location analysis of logistics centres in Laos, *International Journal of Logistics Research and Applications: a Leading Journal of Supply Chain Management* 16(3): 227–242. http://dx.doi.org/10.1080/13675567.2013.812194

Reilly, W. J. 1931. *The Law of Retail Gravitation*. New York, USA.

Rodrigue, J.-P. 2006. Transportation and the geographical and functional integration of global production networks, *Growth and Change* 37(4): 510–525. http://dx.doi.org/10.1111/j.1468-2257.2006.00338.x

Roso, V. 2007. Evaluation of the dry port concept from an environmental perspective: a note, *Transportation Research Part D: Transport and Environment* 12(7): 523–527. http://dx.doi.org/10.1016/j.trd.2007.07.001

Roso, V.; Woxenius, J.; Lumsden, K. 2009. The dry port concept: connecting container seaports with the hinterland, *Journal of Transport Geography* 17(5): 338–345. http://dx.doi.org/10.1016/j.jtrangeo.2008.10.008

Smith, M. W. 1979. The economics of physician location, in *Proceedings of Western Regional Conference of American Association of Geographers*, 1979, Chicago, Illinois, USA.

Weber, A. 1929. *Theory of the Location of Industries*. Translated by C. J. Friedrich from Weber's 1909 book. Chicago: The University of Chicago Press.