A fuzzy data meta training system for ranking hub container terminals

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Abstract

The potential and critical aspects of any transport service can be highlighted through the estimation of appropriate performance indicators of the examined system. Commonly, container terminal analysis is based first on the evaluation and comparison of quantitative parameters that describe the level of service of the terminal and, on the other side by means of performance indicators related to terminal productivity. In this paper a Fuzzy Inference System for evaluation of a synthetic performance indicator is proposed. This tool could help planners and managers in terminals performances analysis and ranking as well as in assessing the effects of possible intervention on the systems. The proposed approach is suitable in the case of hub container ports. In fact this system is characterised by significant uncertainties and it is not always governed by certain rules, rational behaviour, so that it cannot be easily represented by traditional mathematical techniques and models. In our opinion, could be convenient to define the values of the considered parameters by explicitly define them in an approximate way, that is to say by fuzzy sets.

Keywords: Fuzzy Sets, Container Terminals, Level of Service.

1. Introduction

The containerized transport of goods plays a key role for the worldwide economy. Considering the decrease of demand level due to the economic crisis, offering better services to attract shipping companies becomes more and more important for terminal operators. On the other hand, terminal managers have to optimize the low economic resources for investments in infrastructures and employees in order to be competitive. The strategies adopted to remain competitive are various but it is not easy to choose the optimal one. Spot intervention is sometimes not sufficient to increase the potential and ranking of the Container Terminal (CT); besides, the forecasts of future scenarios resulting by combined variation of several management and infrastructural factors is very complex.

In order to evaluate the effects of planned interventions, a lot of basic indicators are usually employed. Generally these indicators are divided into two categories(Van de Lande and Van den Bossche, 2005):

- Quality Indicators (QIs);

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- Performance Indicators (PIs).

QIs are effectiveness indicators of CTs services and are those that matter to shipping companies. This type of indicators may be divided into subcategories such as indicators of punctuality, services frequency, accessibility, safety and security, facility characteristics, etc. Examples of QIs are cut-off time, delay, waiting time, connections to rail or road networks, damage frequency, container area and so on.

The PIs are efficiency indicators concerning the throughput of a CT and are those that matter to terminal operators. Examples of PIs are transshipped TEUs per hour, utilization rate, operational costs and so on.

In this work, we present a method, based on a Fuzzy Inference System (FIS) (Zimmermann 1996) that relates CTs system indicators to an overall measure of port attractiveness.Assuming that the attraction of a given CT, for a generic shipper, is related to CT characteristics, the behaviour of a human decision-maker that has to choose the best CT, or has to rank a group of CT to make his choice, is simulated through a FIS. The proposed soft computing approach takes into account the significant uncertainties and the unknown mathematical relationships between CT characteristics, and quality indicators of terminal services.

The method can be employed both as a benchmarking/ranking procedure and as a decision support system to evaluate future scenarios to improve terminal competitiveness.

2. Background

In literature since the sixties many studies have been developed in order to investigate port competitiveness by mean of indicators. In the 1976's United Nations Conference on Trade and Development (UNCTAD) published a document about port performance indicators. This study is considered by the researchers in this area as a reference, but it considered only two type of indicators: operational and financial performance ones.

During the last twenty years other relevant research projects have been worked out:

- in SIMET (1993) and IMPULSE (1999) projects performance indicators were defined for selected terminal operations;
- in IQ (1998) and LOGIQ (1998) works reliability, flexibility and safety were considered the most critical port quality indicators according to the customer satisfaction;
- in OECD (2002) study *turn-round time,* total time between arrival and departure for all ships divided by number of ships (hours/ship), was adopted as unique port performance measurement;
- Ballis (2004) paper introduced a set of Level of Service (LOS) standards based on quantifiable indicators according to cargo volume, terminal location and access, handlingequipment used, types of modes served, and others with the aim to classify the intermodal terminals.

Hence the performance measurement studies, such as the aforementioned ones, for port classification are made according different types of approaches: Data Envelopment Analysis (DEA) (Wang et al., 2003), Operational Competitiveness Rating Analysis (OCRA) (Parkan, 1994), Game theories, Productivity analysis and Multi-Criteria Decision Making (MCDM) methods (Cullinane et al, 2006, Roll and Hayuth, 1993, Sharma and Yu, 2009, Teng et al., 2004).

DEA and OCRA are non parametric methods based on operational efficiency by taking multiple inputs and outputs as evaluation indicators, but they are confined to few alternative in evaluation. DEA is a mathematical programming technique which computesthe relative efficiency of the evaluated object andcompares it to the frontier. OCRA is similar to DEA. Ituses linear programming approach to establish an analyticmodel. Productivity analysis is to evaluate operationalefficiency. Game theory by applying linear programming consists, in brief, to processquantitative data forcontinuous alternatives. However it focuses on finding some competitive strategies' numerical data from micro viewpoints; thus, this method is not proper for analysing many port considering many criteria. The fifth one, MCDM, cantreat both quantitative and qualitative data, and it includesa wider range of evaluation indicators as well as efficiencyand effectiveness.

Nevertheless the port competitiveness measurement, and consequently port classification, are very complex because of the uncertainty due to the lack of available ports data (imprecise, scarce and vague information), so that it can't be convenient to adopt the traditional mathematical techniques and models.In these cases it could be useful to face the problem using soft computing techniques based on a fuzzy logic inference system.

In literature there are few works that consider the vagueness in freight transportation and even less in CTs classification(Chou, 2007 and 2010; Huang *et al.*, 2003). However it is relevant to notice that Chou (2007 and 2010) e Huang *et al.* (2003) apply MCDM method together with fuzzy feature of indicators. In the port classification it may be deemed appropriate to focusing upon fuzzy approach.

3. Problem Statement and methodology

The objectives of shipping companies are to minimize the transport costs to obtain fast and effective services, that is the CT should have high QIs values. A concise indicator of terminal QIs could be defined as port Level of Attractiveness (LA) (i.e. level A, level B, level C,…). The higher is the level of the CT, the higher is its rank position in shipping companies evaluation.

To evaluate the LA the analyst needs a method that relates LA to a part or all of terminal quality indicators.Starting from a set of inputs indicators, the proposed model has as output the CT Level of Attractiveness.

3.1 FIS input and output parameters

The inputs of the FIS are the *characteristics* c_i with $i \in [1, 2, \dots n]$ of a CT, the output is the Level of Attractiveness p of a terminal. The possible values of c_i and p are defined into respective bounded definition sets ($c_i \in Sc_i$, $p \in Sp$).

As regards terminal characteristics, their choice is essential for a proper representation of the problem. Characteristics choice must achieve a balance between the necessitate to consider many possible aspects of the problem and the need to limit the number of input parameters, in order to make feasible algorithm calibration. For an immediate and easy applicability of the methodology, chosen features have to be represented in numerical form, and corresponding data must be available with relative ease. From the methodological point of view, the choice of such characteristics, needs to be conducted on the basis of "expert" assessments by specialists, or at least on the basis of detailed analysis of dynamics that determine the attractiveness for the market of a Container

Terminal. This approach can be validated on the basis of evaluations on the goodness of results provided, as well as through features sensitivityanalysis.

Given the definition sets Sc_i for c_i and Sp for p, in the proposed method each one is divided respectively into x fuzzy subsets $I_{i,v}$ with $v \in [1, 2, \dots x]$and into x fuzzy subsets O_v .

Differently from the classical logic, in fuzzy logic a value belongs to a set with a certain degree of membership defined in the *interval* [0, 1], rather than to the *set* {0, 1}. Each fuzzy subset is defined by a linguistic value that is “low”, “high”, “short”, “long”, etc.In the current case, given x LA, the linguistic judgment corresponding to each fuzzy subset is just the corresponding LA.

The degree of membership to a set is defined by a *membership function (MF)*. In this framework a value c_i^* belongs to a subset $I_{i,v}$ depending on the membership function $\mu_{i,v}(c_i) \in [0, 1]$ and, in the same way, a value p^* belongs to a subset O_v depending on the membership function $\mu_v(p) \in [0, 1]$. The more a value belongs to a LA, the more the degree of membership is near to one. Given a shape for each MF, they may be identified by their typical parameters. For example a triangular or a trapezoidal shape can be defined by the position of the vertexes.

For example if c_1 is the number of quay cranes, assuming to classify CTs according to 3 QLs (x = 3), $I_{1,1}$ would represent the degree of membership to “Level C”, $I_{1,2}$ to “Level B” and $I_{1,3}$to “Level A”, where level A means the level of facilities with higher power of attractiveness, and level C being the lower. For triangular membership functions the fuzzy subsets can be defined as depicted in Fig. 2.In this way a CT with eight quay cranes ($c_1 = 8$) is “level C” with a degree of membership equal to $\mu_{1,1}(8)$ = 0.8and is“Level B” with a degree of membership equal to $\mu_{2,1}(8)$ = 0.2; in other words, eight quay cranes belong more to the subset “Level C” than to the subset “Level B” and do not belong to the subset “Level A”.

The choice of MF functional shape can also be made on the basis of expert assessments, to be subsequently validated on the basis algorithm outputs. In general functional forms characterized by a low number of parameters have to be preferred. They allow to reacha good balance between the number of parameters to be calibrated, and, at the same time, a precision level consistent with the fuzzy approach chosen for problem representation.

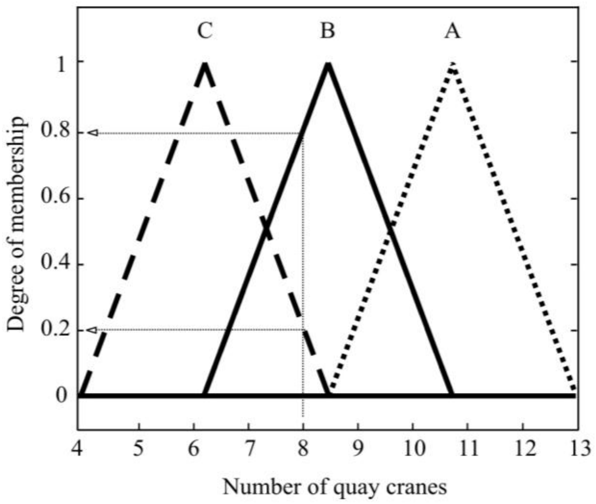

Figure 1: Membership functions of Number of cranes

3.2 FIS aggregation rules

The set of characteristics is related to the Level of Attractiveness through a *Fuzzy Inference System (FIS).*

A *Fuzzy Inference System* simulates the behavior of a human decision-maker with rules like:

if *V is X* ***then*** *W is Y*

Within the Fuzzy Logic framework, this rule means "the more V is X, the more W is Y", and the variables X and Y can assume linguistic or approximate values, in other words, fuzzy sets. The degree of truth of a given rule depends on the fuzzy sets, defined by their respective membership functions.

Generally the number of Terminal Container characteristics *n* is greater than one.

The choice of FIS combination rules is based on expert assessments regarding features selected for CT classification. In general, parameters contributing to LA increase will be combined according to AND logical rule, whileparameters contributing in alternative manner can be combined according to OR rule. Parameters, whose presence is detrimental to CT attractiveness, may be combined with others with NOT condition.

The proposed model is a FIS with different rules; each rule may consider all or a portion of *n* characteristics in the if-then statements with one type or different logical fuzzy operators.The general formof a rule with, as an example, the only AND operator can be summarized as follows:

$$\textbf{\textit{IF}}\ c_1 \text{ is } I_{1,1}\ \textbf{AND}\ c_2 \text{ is } I_{2,1}\ \textbf{AND}\ c_3 \text{ is } I_{3,1} \ldots\ \textbf{AND}\ c_n \text{ is } I_{n,1}\ \textbf{\textit{THEN}}\ p \text{ is } O_1$$

……………………

$$\textbf{\textit{IF}}\ c_x \text{ is } I_{1,x}\ \textbf{AND}\ c_2 \text{ is } I_{2,x}\ \textbf{AND}\ c_3 \text{ is } I_{3,x} \ldots\ \textbf{AND}\ c_n \text{ is } I_{n,x}\ \textbf{\textit{THEN}}\ p \text{ is } O_x$$

3.3 FIS Results

Since the result of a rule is a fuzzy set, to define a crisp (non fuzzy) output of the FIS, it is necessary to defuzzify the output for example considering the barycentric value of the output area (Fig. 2). For detailed implication and defuzzification methods see Zimmermann (1996).

3.4 FIS Specification: The fuzzy data meta training method

In order to obtain reliable results the proposed model requires adequate calibration. This process, once fixed the features to be taken as input parameters, input and output MFs shape and logical rules to be applied, will concentrate on MF characteristic parameters.A well-established MF construction methodologies is based on the development of responses to questions provided by experts to a questionnaire. Actually, in this case the FIS can be considered as an expert systems since the MF specification come from direct knowledgeprovided by stakeholders.

In this case, for example, to define the shape of the membership function of the number of quay cranes related to a certain terminal Level of Attractiveness, the possible questions are:

1) "In your opinion, for a container terminal with LA "A", the number of quay cranes is definitely "optimal" if it is included between which values?"
2) "In your opinion, for a container terminal with LA "B", the number of quay cranes is "optimal" if it is at least greater than which value?"
3) "In your opinion, for a container terminal with LA "C", the number of quay cranes is "optimal" if it is at least less than which value?"

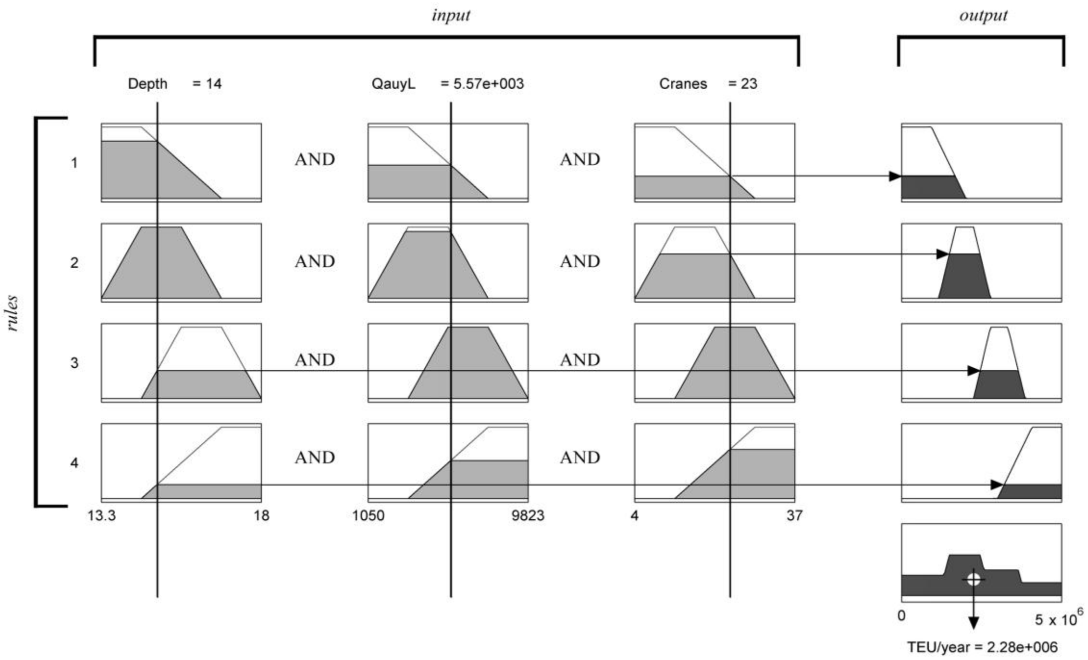

Figure 2: FIS (defuzzification)

Starting from the answers to the first question it is possible, assuming trapezoidal or triangular shaped MFs, to define the upper vertexes of $\mu_{A,c*}$as they refer to the maximum degree of membership. In other words the value of the membership function in these points is equal to one. The second and the third question allow in the same way to find the lower vertexes of the membership function $\mu_{A,c*}$. In the same way the answers to the second question define the upper vertexes of $\mu_{B,c*}$, while the first and third characterize the lower vertexes of the same MF, and so on. Of course, the values considered in this simple case will be the medium values of the answers of the experts involved.

If we no expert knowledgeis available or used, then the calibration procedure is based on the construction of an Adaptive Neural Fuzzy Inference System (ANFIS) for MF calibration (Jang, 1993). The approach is based on correlation of c_i^* values for a sample of CTs, with corresponding p^* values. To do this, a measurable parameter has to be taken as indicator of membership to a certain LA for a given CT.This procedure needs, however, relevant amount of data to perform the calibration.

If a data set is available but not enough large for using classical ANFIS technique calibration-validation, then a different procedure for MF construction, based on available data and on exploitation of uncertainty, is here proposed. Again the calibration process should correlate c_i^* values with correspondingp^*values, referred to a parameter taken as membership indicator for a CT to a certain LA.

The proposed Fuzzy Data Meta-Training calibration procedure (FDMT) is performed through the following phases:

1) definition, starting from available data, of definition sets Sc_i for each c_i and $Sp$for p;
2) if we denote respectively with c_i^{max} and c_i^{min} maximum and minimum values of c_i characteristic, considering x QL, assigning $\delta = c_i^{max} - c_i^{min}$, each Sc_i is divided into x subsets:

$$\mathrm{Sc}_i^1 = \{ c_i^* | \, c_i^{min} \leq c_i^* \leq c_i^{min} + (\delta / x) \}$$

$$\mathrm{Sc}_i^2 = \{ c_i^* | \, c_i^{min} + (\delta/x) \leq c_i^* \leq c_i^{min} + 2\cdot(\delta/x) \}$$

…………………………

$$\mathrm{Sc}_i^x = \{ c_i^* | \, c_i^{min} + (\delta/x) \leq c_i^* \leq c_i^{min} + x\cdot(\delta/x) \}$$

In the same way denoting p^{max} and p^{min} and$\Delta = p^{max} - p^{min}$:

$$\mathrm{Sp}^1 = \{ p^* | \, p^{min} \leq p^* \leq p^{min} + (\Delta/x) \}$$

$$\mathrm{Sp}^2 = \{ p^* | \, p^{min} + (\Delta/x) \leq p^* \leq p^{min} + 2\cdot(\Delta/x) \}$$

………………………

$$\mathrm{Sp}^x = \{ p^* | \, p^{min} + (\Delta/x) \leq p^* \leq p^{min} + x\cdot(\Delta/x) \}$$

3) a fuzzy set $I_{i,v}$ whose MF$\mu_{i,v}(c_i)$ has a trapezoidal shape, is associated to each of these subsystems. The trapezoid vertex are identified as follows:

$$\upsilon_{i,1} \{ (c_i^{min}; 0), (c_i^{min}; 1), (c_i^{min} + \delta/x; 1), (c_i^{min} + 3\delta/x; 0) \}$$

…………………………

$$\upsilon_{i,v} \{ (c_i^{min} + (v-2)\cdot\delta/x; 0), (c_i^{min} + (v-1)\cdot\delta/x; 1), (c_i^{min} + v\cdot\delta/x; 1), (c_i^{min} + (v+1)\cdot\delta/x; 0) \}$$

…………………………

$$\upsilon_{i,x} \{ (c_i^{max} - 3\delta/x; 0), (c_i^{max} - \delta/x ; 1), (c_i^{max}; 1), (c_i^{max}; 0) \}$$

in the same manner for O_w subsystems end their MF $\mu_v(p)$:

$$\upsilon_1 \{ (p^{min} - \gamma; 0), (p^{min} - \gamma; 1), (p^{min} + \Delta/x; 1), (p^{min} + 3\Delta/x; 0) \}$$

…………………………

$$\upsilon_v \{ (p^{min} + (v-2)\cdot\Delta/x; 0), (p^{min} + (v-1)\cdot\Delta/x; 1), (p^{min} + v\cdot\Delta/x; 1), (p^{min} + (v+1)\cdot\Delta/x; 0) \}$$

…………………………

$$\upsilon_x \{ (p^{max} - 3\Delta/x; 0), (p^{max} - \Delta/x ; 1), (p^{max}; 1), (p^{max} + \tau; 0) \}$$

where γ and τ are range increasing factors on the defuzzification methodology indicated in the paragraph 3.3.

4) These MF, generated assuming a uniform correlation between LAs and c_i, may be used to compare FIS p_{fis}^* values with p^*values coming from calibration database. If results coming out from such comparison process are satisfactory, the calibration process may be stopped here.
5) Otherwise, a vertexes adjustment process, based on a more detailed analysis of available data, must be implemented. Given a database with k CTs, let $S_j = (c_1^*, c_2^*, ..., c_n^*, p^*)_j$ with $j \in [1, 2, \dots k]$ a set of values referred to a certain CT.
   Given a subsetσ of this set, composed by data vectors for which it is:

$$\sigma = \{S_j \mid p^*j \in Sp^1\}$$

   for this subset we can calculate, for each characteristic the maximum and minimum values $c_i^{max}{}_{(\sigma)}$ and $c_i^{min}{}_{(\sigma)}$.
   Corresponding MFs vertex will undergo the following change of coordinates:

$$\upsilon_{i,1}\ \{(c_i^{min}{}_{(\sigma)};1),(\ c_i^{min}{}_{(\sigma)} + \delta\ /x\ ;\ 1),(\ c_i^{min}{}_{(\sigma)} + 2\cdot\delta\ /x\ ;\ 0),(c_i^{max}{}_{(\sigma)};0)\}$$

   Likewise, for others x MF, for all n CT characteristics.

4. Description of FIS algorithm for Mediterranean sea Hub Container Terminal benchmarking

The proposed method has been applied to a real case study. The aim of the application is the classification of the principal Mediterranean sea container terminals (HUB) based on their attractiveness for shipping operators.

The classification is based on 4 levels (A, B, C, D) representative, in descending order, of terminal attractiveness. The selection of characteristics to be considered was made on the basis of assessments made by expert analysts. These characteristics have to be considered as a first set relevant to phenomenon representation, which may eliminate, or further increase in number, depending on input parameters sensitivity analysisand model validation processes which will be described below.

The proposed FIS can be defined differently (different output type, number of rules, shape and number of Membership Functions) as a function of the calibration procedure itself. In particular, the proposed case study will be calibrated both with ANFIS technique and the procedure described in the paragraph 3.4.

4.1 Input and output characteristics

Regardless of the calibration procedure among many possible, 8 characteristics, shown in Table 1, have been selected.We highlight that only for convenience of calculation and uniform representation of the FIS rules the parameter value c_7 is equal to $c_7 = |\ d_p - 350\ |$,where 350 correspond to the distance of the port as far away from Gibraltar – Suez course.

Table 1. Input variables

Categories	*i*	c_i	*units*
Facilities	1	Maximum water draft	meter
	2	Quay length	meter
	3	Stacking area	square meter
	4	Quay cranes	number of cranes
Services	5	Connected HUB ports	number of ports
	6	Connected ports	number of ports
Location/Inland	7	Distance of port position from Gibraltar-Suez course	nautical miles
	8	Rate of transshipment TEUs	%

The FIS output has been chosen equal to the number of TEUs handled in one year at the considered container terminal.

Lacking in this phase of the research questionnaires of the type described in section 4.4, for algorithm calibration and validationa database referred to 18 ports has been considered (Table 2). For each of them $c_i^*$and p^* values have been collected.

4.2 Calibration with ANFIS technique

For each of the 8 input variables two Gaussian MFs were considered. The choice of the Gaussian MF type was carried out in order to minimize the parameters involved (two for each Gaussian), because of the small sample used to calibrate the system. The variation range for each input was defined as the minimum and maximum value for each characteristic, calculated on Table 2 data. Similarly, the variation range of the output was taken equal to the variation range of the TEU/year in Table 2.

Table 2. Database for FIS calibration and validation

Port	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	p
Valencia	16	4162	1365420	30	10	27	210	0.44	3602112
GioiaTauro	18	3395	1700000	30	14	44	284	0.93	3467772
Algeciras	17	9823	866132	37	10	19	350	0.95	3324310
Port said est/west	16.5	2400	1242000	19	10	20	350	0.87	3257984
Barcelona	16	4065	908000	17	12	40	141	0.39	2569549
Malta Freeport	17	2426	683000	23	14	57	344	1.00	2330000
Genoa	15	4141	1619355	18	12	31	0	0.08	1766605
Piraeus	18	2774	626000	14	13	39	172	0.61	1403408
Haifa	14	1360	500000	12	11	28	181	0.41	1395900
Alexandria/El Dekh	14	2045	571304	8	14	38	318	0.08	1259000
Damietta	14.5	1050	254231	10	10	20	350	0.74	1236502
Izmir	14.5	1050	295000	5	14	43	5	0.13	884000
Mersin	14	1470	1100000	5	14	35	11	0.10	868000
Marseille	14.5	2127	560000	13	14	41	75	0.00	847651
Ashdod	15.5	2850	500000	11	11	26	225	0.00	827900
Taranto	15	1500	650000	10	7	20	178	0.90	786655
Lattakia	13.3	4280	500000	4	10	29	40	0.17	570000
Cagliari	16	1580	435000	7	13	43	280	0.40	252837

Having to calibrate the FIS according to ANFIS technique, it was set a single tone output type (Sugeno FIS Type). Four macro levels of output were considered (A, B, C, D) dividing the variation range of output in four equal parts. A number of 256 rules have been set (see Table 3) resulting from all possible combinations of input values (2 levels for each input). Consequently, each macro level of output has been divided into 64 intermediate levels for A, B, C and D level of attractiveness (i.e. A_1, A_2,... A_{64}; B_1, B_2, ...,B_{64}; C_1, C_2,... C_{64}; D_1, D_2,... D_{64}).

From the provided sample (Table 2) were selected 10 ports for training phase and the remaining 8 ones for the checking phase. The ten selected ports are referred on average to the whole variation range of the output. The selected number of the training epochs is 10.

The final training error obtained is very low and equal to 2.4 10^{-5}. That is the system reproduces exactly the training data. As expected, given the low number of ports with available data compared to the number of considered variables, FIS calibrated using this procedure has little chance of being generalized as the mean square error on TEU/year output related to the checking ports account is equal to about 92%.

Table 3. Excerpt of rules structure

N.	Rule
1	***IF*** $c_1$is*Level A* **AND** $c_2$is*Level A* **AND** $c_3$is*Level A* **AND** c_4 is*Level A* **AND** c_5 is*Level A* **AND**c_6 is*Level A* **AND** c_7 is*Level A* **AND** c_8 is*Level A* ***THEN*** *LA is "A"*
2	***IF*** $c_1$is*Level A* **AND** $c_2$is*Level A* **AND** $c_3$is*Level A* **AND** c_4 is*Level A* **AND** c_5 is*Level A* **AND**c_6 is*Level A* **AND** c_7 is*Level A* **AND** c_8 is*Level B* ***THEN*** *LA is "A_2"*
3	***IF*** $c_1$is*Level A* **AND** $c_2$is*Level A* **AND** $c_3$is*Level A* **AND** c_4 is*Level A* **AND** c_5 is*Level A* **AND**c_6 is*Level A* **AND** c_7 is*Level B* **AND** c_8 is*Level B* ***THEN*** *LA is "A_3"*

4.3 Calibration with Fuzzy Data Meta Training (FDMT)

The definition sets of each of the 8 characteristic have been split into 4 fuzzy equispaced subsystems, one for each LA (A, B, C, D), represented by 4 MF with trapezoidal shape. With respect to the variable number of cranes, in Figure 3 an example of input MFs have been represented.

The trapezoidal shape was chosen because is well suited to represent more or less wide intervals in which the degree of membership takes a maximum value, as expected in a classification procedure.

The variation ranges of input parameters were defined as in the previous paragraph. In the same way to the MFs for the input, we created four trapezoidal functions corresponding to four LA output.

Characteristics combination logical rules implemented (4 rules) are shown in Table 4. In this case characteristics chosen are all contributing to increase CT performance and attractiveness, so they were combined using the AND operator.

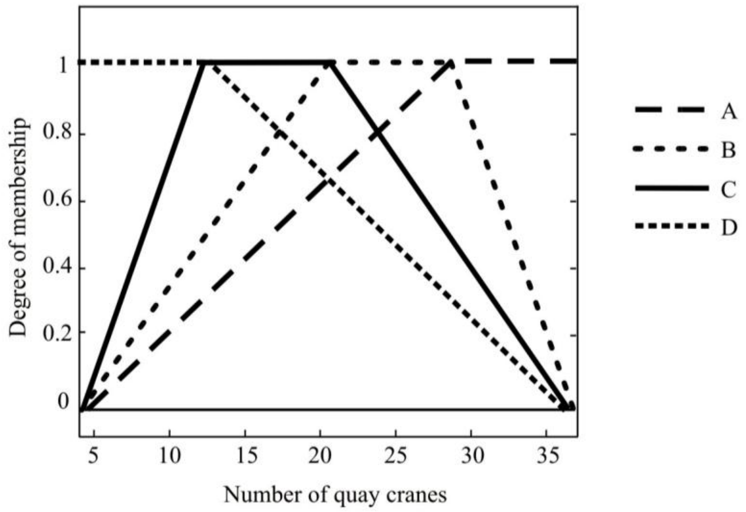

Figure 3: Membership functions of Number of cranes (FDMT starting point)

This starting point is established on the basis of rational and logic assumption (i.e. expertise). Consequently, the proposed FIS need a calibration and validation procedure that take advantages from the assumed starting point. The calibration aims to move the vertices of the upper bases of the trapezoidal shape MFs according to the methodology proposed in paragraph 3.4.

Table 4. FIS logical rules

N.	Rule
1	***IF*** c_1 is *Level A* **AND** c_2 is *Level A* **AND** c_3 is *Level A* **AND** c_4 is *Level A* **AND** c_5 is *Level A* **AND**c_6 is *Level A* **AND** c_7 is *Level A* **AND** c_8 is *Level A* ***THEN*** *LA is "A"*
2	***IF*** c_1 is *Level B* **AND** c_2 is *Level B* **AND** c_3 is *Level B* **AND** c_4 is *Level B* **AND** c_5 is *Level B* **AND** c_6 is *Level B* **AND** c_7 is *Level B* **AND** c_8 is *Level B* ***THEN*** *LA is "B"*
3	***IF*** c_1 is *Level C* **AND** c_2 is *Level C* **AND** c_3 is *Level C* **AND** c_4 is *Level C* **AND** c_5 is *Level C* **AND** c_6 is *Level C* **AND** c_7 is *Level C* **AND** c_8 is *Level C* ***THEN*** *LA is "C"*
4	***IF*** c_1 is *Level D* **AND** c_2 is *Level D* **AND** c_3 is *Level D* **AND** c_4 is *Level D* **AND** c_5 is *Level D* **AND**c_6 is *Level D* **AND** c_7 is *Level D* **AND** c_8 is *Level D* ***THEN*** *LA is "D"*

4.4 FDMT results

Table 5 shows the comparison between results obtained from calibrated and non-calibrated FIS and those expected from the starting database. In particular, considering surveyed port container throughput (*DB*), expected Levels of Attractiveness have been calculated (*EL*). These levels have been compared with the levels provided by the non-calibrated FIS (*NC-FIS LA*) and with those obtained after FDMT calibration (*C-FIS LA*). The FIS provides a crisp output, numerically associated to TEUs throughput per year; these values, for both non-calibrated (*NC-FIS*) and calibrated FIS (*C-FIS*) have been compared with real data, in order to calculate the percentage error (*NC-FIS error* and *C-FIS error* respectively).

LA calculated with the proposed procedure (*C-FIS LA*) match the expected ones in 16 out of 18 cases, while the mean percentage error on the number of TEUs/year handled is about 30.0 %.

As expected, the small number of data used for calibration, compared with the number of features considered, leads to results characterized by a relevant, though not excessive, mean percentage error. However the proposed methodology allows to obtain the required information, namely to assign a given port to the right class, according to its relevant characteristics, with a high level of accuracy. In conclusion, given the complexity of the problem, and the lack of available data, the proposed approach can still provide useful information for the analyst, with an appropriate degree of accuracy.

Table 5.FDMT output results

Port	*DB* [TEU/year]	*EL*	*NC-FIS* [TEU/year]	*NC-FIS LA*	*NC-FIS error*	*C-FIS* [TEU/year]	*C-FIS LA*	*C-FIS error*
Valencia	3602112	A	1881700	C	47,8%	3427700	A	4,8%
GioiaTauro	3467772	A	3462900	A	0,1%	3427700	A	1,2%
Algeciras	3324310	A	1881700	C	43,4%	3427700	A	3,1%
Port said est/west	3257984	A	1881700	C	42,2%	3427700	A	5,2%
Barcelona	2569549	B	2516100	B	2,1%	1706600	C	33,6%
Malta Freeport	2330000	B	1881700	C	19,2%	2383700	B	2,3%
Genoa	1766605	C	1881700	C	6,5%	1506500	C	14,7%
Piraeus	1403408	C	1881700	C	34,1%	1709300	C	21,8%
Haifa	1395900	C	230030	D	83,5%	639040	D	54,2%
AlexandriaEl Dekh	1259000	C	1881700	C	49,5%	1506500	C	19,7%
Damietta	1236502	C	1881700	C	52,2%	1506500	C	21,8%
Izmir	884000	D	1881700	C	112,9%	473130	D	46,5%
Mersin	868000	D	1881700	C	116,8%	473130	D	45,5%
Marseille	847651	D	1881700	C	122,0%	451950	D	46,7%
Ashdod	827900	D	274730	D	66,8%	451950	D	45,4%
Taranto	786655	D	1881700	C	139,2%	451950	D	42,5%
Lattakia	570000	D	105260	D	81,5%	451950	D	20,7%
Cagliari	252837	D	1881700	C	644,2%	531050	D	110,0%

The final calibrated FIS configuration is described by MFsas in example given in Figure 3 with the vertexes coordinates shown in Table 6 and by the set of rules reported in Table 4.

4.4 Characteristics sensitivity analysis

In order to assess how each FIS input parameter influences the results, sensitivity analysis was carried out. Starting from the configuration of the algorithm described in Section 4.3, all c_i possible combinations, obtained by reducing the number of parameter, were considered. For each combination the number of errors provided by the corresponding algorithm has been evaluated. The results of this analysis are shown in Figure 4. Where each cross shows the number of wrong output (i.e. wrong level of attractiveness) obtained for each number and combination of input parameters. For example, considering seven parameters, the eight possible combinations without repetitions lead to 2 or 3 or 4 wrong LA. In all cases, the number of the rules (four) does not change (the rules are always those shown in the Table 4). Thus, Figure 4 summarizes the results of the sensitivity analysis showing only the number of wrong output LA. Actually for each number and for each combination of input parameters it has been also calculated the related errors of FIS output with respect to TEUs throughput values coming from the starting database. These errors allow to consider also the difference between the output levels. The combination with the minimum number of input parameters and at the same time with the lowest errors on TEUs throughput values is the one with only 3 parameters (number of quay cranes c_4, number of connected ports c_6 and port distance from Gibraltar-Suez route c_7).Such a result, if confirmed by further studies and extensive research, would reduce the amount of data required for model application and at the same time make it much easier its calibration.

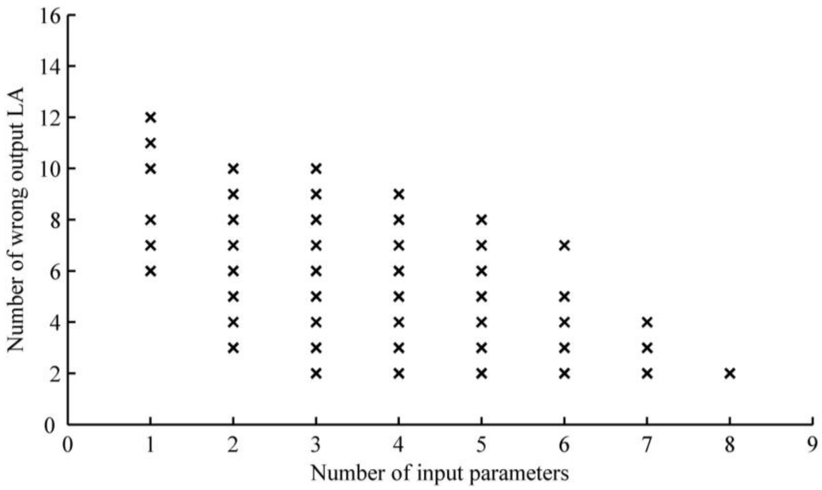

Figure 4: Characteristics sensitivity analysis

5. Conclusions and further developments

The proposed methodology allows to determine a synthetic index that can evaluate the attractiveness of a given Container Terminal for shipping lines, starting from a set of parameters representative of its main characteristics.

The FIS classification procedure may provide useful results for evaluating comparatively the performance of different CTs. The approach based on fuzzy Level of Attractiveness, makes it possible to get information with a degree of approximation sufficient and useful for analysis purposes, even in presence of uncertainty of results due to the high number of calibration parameters and, at the same time, to a low number of calibration data.

The method can be employed as a decision support system to evaluate future scenarios with respect to intervention aimed to improve terminal competitiveness. In the case of Taranto Container Terminal, has been estimated that the increase of one level (from Level D to Level C) may be achieved by increasing the number and quality of feeder services (see port connections), and improving road and rail links with the port. The new classification could lead to a potential increase in demand attracted.

To enhance model predictive capabilities, an approach that seems to be promising is to consider time series of calibration data. This approach, combined also with future collection of such data, according to standardized criteria and methodologies, may make the classification algorithm dynamically updatable and increase its robustness in scenarios foreseeing.

Further developments of this research will involve application of the methodology for classification of Container Terminals located outside the basin of the Mediterranean Sea and selection of input characteristic parameters and calibration of MFs on the basis of questionnaires completed by experts and professionals in the field of container transport.

Table 6. Values of Vertexes of calibrated trapezoidal MFs.

LA	*vertex*	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	p
D	$\upsilon_1(1)$	(0; 13.3)	(0; 1050)	(0; 254230	(0; 4)	(0; 7)	(0; 19)	(0; 0)	(0; 0)	(0; -2000000)
	$\upsilon_1(2)$	(1; 13.3)	(1; 1050)	(1; 295000)	(1; 4)	(1; 7)	(1; 20)	(1; 5)	(1; 0)	(1; 252840)
	$\upsilon_1(3)$	(1; 16)	(1; 4280)	(1; 1100000)	(1; 13)	(1; 14)	(1; 43)	(1; 280)	(1; 1)	(1; 884000)
	$\upsilon_1(4)$	(0; 16.825)	(0; 7629.8)	(0; 1338600)	(0; 28.75)	(0; 14)	(0; 47.5)	(0; 280)	(0; 0.9)	(0; 2764800)
C	$\upsilon_2(1)$	(0; 13.3)	(0; 1050)	(0; 254230)	(0; 4)	(0; 7)	(0; 19)	(0; 0)	(0; 0)	(0; 252840)
	$\upsilon_2(2)$	(1; 14)	(1; 1050)	(1; 254230)	(1; 8)	(1; 10)	(1; 20)	(1; 0)	(1; 0.08)	(1; 1236500)
	$\upsilon_2(3)$	(1; 18)	(1; 4141)	(1; 1619400)	(1; 18)	(1; 14)	(1; 39)	(1; 350)	(1; 0.74)	(1; 1766600)
	$\upsilon_2(4)$	(0; 18)	(0; 7629.8)	(0; 1619400)	(0; 28.75)	(0; 14)	(0; 47.5)	(0; 350)	(0; 0.75)	(0; 2764800)
B	$\upsilon_3(1)$	(0; 14)	(0; 2426)	(0; 615670)	(0; 12)	(0; 9)	(0; 29)	(0; 88)	(0; 0)	(0; 1090200)
	$\upsilon_3(2)$	(1; 16)	(1; 2426)	(1; 683000)	(1; 17)	(1; 12)	(1; 40)	(1; 141)	(1; 0.39)	(1; 2330000)
	$\upsilon_3(3)$	(1; 17)	(1; 4065)	(1; 908000)	(1; 23)	(1; 14)	(1; 57)	(1; 344)	(1; 1)	(1; 2569500)
	$\upsilon_3(4)$	(0; 18)	(0; 9823)	(0; 1700000)	(0; 37)	(0; 14)	(0; 57)	(0; 350)	(0; 1)	(0; 3602100)
A	$\upsilon_4(1)$	(0; 14.475)	(0; 2400)	(0; 615670)	(0; 12.25)	(0; 8.75)	(0; 19)	(0; 87.5)	(0; 0.25)	(0; 1090200)
	$\upsilon_4(2)$	(1; 16)	(1; 2400)	(1; 866130)	(1; 19)	(1; 10)	(1; 19)	(1; 210)	(1; 0.44)	(1; 3258000)
	$\upsilon_4(3)$	(1; 18)	(1; 9823)	(1; 1700000)	(1; 37)	(1; 14)	(1; 44)	(1; 350)	(1; 0.95)	(1; 3602100)
	$\upsilon_4(4)$	(0; 18)	(0; 9823)	(0; 1700000)	(0; 37)	(0; 14)	(0; 57)	(0; 350)	(0; 1)	(0; 5763400)

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